

Narrative Cacophony in Financial Markets*

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Abstract

I develop a methodology for extracting “narratives – endogenously-emerging interpretational patterns – from unstructured text. I define “narrative cacophony” as the presence of many salient narratives with contradictory pricing implications. Applying the methodology to 21,771 news articles from the 2025 tariff “Liberation Day” episode, I study how cacophony mediates the incorporation of public information. I document that cacophony dampens trade volume. Moreover, when there is less trade because of cacophony, narratives explain a smaller share of variation in daily returns. The incorporation of narrative information also slows and a delayed pricing-in effect obtains. Because markets update prices through agents’ trades in the presence of disagreement, these findings suggest that information that is difficult to interpret (as captured by cacophonous narratives) is less well-incorporated by markets as agents are more reluctant to trade.

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1 Introduction

Markets aggregate information into prices. Though the information itself is so vast as to be unobservable in its totality by any single agent, the market recovers it – fragment by fragment, trade by trade – from every decision of every market participant (Hayek, 1945). Abounding evidence suggests this process is so efficient that prices fully reflect all publicly-available information (Cowles, 1933; Fama, 1970). Yet, in a foundational work, Roll (1988) found that a mere 20% of daily stock returns were explainable by ex-post public information. While there is no formal contradiction between these findings, these results are still puzzling: their reconciliation requires that markets not be strongly driven by public news.

This paper proposes a conceptually new angle with which to study the puzzle: the interpretation of information. Public information does not translate into prices mechanically. Before markets can incorporate information, agents must first interpret it. This involves deciding which facts matter, how they fit together, and what they imply about the future. Interpretation itself can be non-trivial. Consider, for example, a piece of information such as the announcement of new tariffs: is it the start of a prolonged trade war? or a swift and productive negotiation? something else altogether? The underlying information is the same. The interpretations – and hence pricing implications – the information gives rise to are strikingly different. Do agents’ interpretations of public information (i.e., *narratives*) mediate how markets incorporate public information?

I conjecture a novel hypothesis for when and why markets aggregate information imperfectly: when public information is difficult to interpret, agents trade less, and – following the Hayekian intuition – markets fare worse at incorporating this information as a result. As in the previous example, interpretation is challenging when there are (i) many salient narratives which (ii) disagree in their pricing implications, a situation I call a *cacophony*. I test the narrative cacophony hypothesis in the context of the “Liberation Day” tariff episode of 2025 (April 1 - July 31).¹

To test the hypothesis, I proceed in three steps. I first develop a theory and an algorithmic methodology for measuring narratives – prevailing interpretations – present in a corpus of natural texts (e.g., news articles), designed so that the number, size, and substance of the narratives emerge endogenously from the data. Second, I elicit each narrative’s daily information content about the severity of tariff-induced price impacts, as well as industries’ exposure to each narrative, and use these to obtain each narrative’s contribution to stock returns on the industry-day level. From these narrative contributions to returns, I construct a novel, market-based measure of *narrative cacophony*: I take cacophony to be the product of narrative *dispersion* (an inverse measure of narrative concentration) and *directional disagreement* (the net share of narrative-implied price pressure), each of which is likewise defined at the industry-day level. Third, I show that narra-

¹On April 2, 2025, President Trump announced broad tariffs against many of America’s trade partners. For the next four months, amidst changing tariff schedules, continuous press coverage, and high economic stakes, investors had to make sense of the new tariff regime. (By the end of July, trade deals with negotiating partners like the EU were firmly on the horizon.) Crucially, exactly the same public information admitted a wide range of conflicting interpretations. Indeed, one may expect the qualitative results of the analysis of this episode to generalize to any informational environment characterized by similarly high stakes and multiplicity of interpretations, including but not limited to monetary policy surprises, geopolitical shocks, and technological revolutions (e.g., the introduction of AI).

tives and narrative cacophony shape how markets aggregate public information. I document that narrative cacophony dampens trade volume (a one-standard-deviation increase in both narrative dispersion and directional disagreement corresponds to 5% lower volume), a result difficult to rationalize with traditional models of disagreement. Furthermore, when the share of trade foregone due to cacophony is high, the share of variation in returns explained by narrative-induced beliefs falls: passing from the quartile of lowest to highest cacophony decreases the R^2 from 25.58% to 0.45%.² Moreover, stock-days on which narrative cacophony suppresses volume are slower to incorporate pricing implications from past narratives' signals (with the lowest quartile of stock-days by cacophony-stifled volume showing essentially no relationship between past narratives to returns, and the highest quartile exhibiting a momentum effect, with a pass-through rate of about half). Because markets aggregate information and update prices through agents' trades in the presence of disagreement, these findings suggest that information which is difficult to interpret (as measured by the presence of cacophonous narratives) is less well-incorporated by markets as agents are more reluctant to trade.³

I now detail these three main steps. First, the paper proposes a conceptual framework and implementation algorithm for the study of narratives. The methodology begins from two theoretical primitives. A *story* is defined as a finite, chronologically ordered list of statements. A *narrative* is a cluster of stories that are *similar in meaning*. The goal of the narrative-extraction pipeline is to start from a corpus of natural texts, extract each text's story, and group stories into narratives. The pipeline (i) summarizes each article into a story using an LLM (the sole LLM intervention of the methodology). The pipeline then (ii) scores the similarity of every pair of stories. To measure story-similarity, I propose a model of story comparisons which evaluates matches between constituent statements using embedding-derived cosine similarity.⁴ Matches of constituent statements are then aggregated to the story level using an *optimal alignment* rule which exploits the trade-off between the quantity and quality of matches, and leverages an additive aggregation rule of Rusonik & Samuelson & Gilboa (2026). Using these story-level similarity scores and the Leiden community-detection algorithm (Traag et al., 2019), the methodology (iii) partitions the set of stories into narrative clusters, such that stories are similar within narratives, and dissimilar across. The Leiden algorithm does not ex ante specify the number or size of narratives, and takes as inputs only the similarity scores, so there is no selection or specification of narrative contents.

I apply the narrative-extraction methodology to a corpus of 21,771 news articles from the US, Canada, Europe and Asia from the "Liberation Day" tariff episode, and obtain a characterization of the narratives which animated discourse at the time. I retain the 14 most prominent narratives by size (as the 14 together cover over 50% of all news articles and each contain at least 200 articles;

²CAPM also explains less of the variation in stock prices: passing from lowest to highest cacophony quartiles reduces R^2 from 55.1% to 28.6%.

³In a series of placebo tests, I verify that these results cannot be explained by a difference between high and low trading volume stock-days alone.

⁴An embedding maps every statement into a very high-dimensional vector space, with dimensionality sufficient to capture semantics, and similarity is given by the cosine of the angle between the two vectors. See, e.g., Hanley and Hoberg (2010); Hoberg and Phillips (2016) for early adopters in finance.

see Figure B.4) and construct the 15th, which is a catch-all pooling of the remaining narratives and singletons. Except the initial LLM summary, the algorithm is fully deterministic and reproducible. The result is a set of coherent, endogenously-emergent narratives, each representing a different interpretation of the Liberation Day episode with its attendant economic consequences. Among these are a narrative on the imminence of a trade-war-induced recession, one on the possibility of US-EU negotiations devolving into retaliatory tariffs, and another on the likelihood and consequences of constitutional challenges to tariff policy. The narrative-extraction methodology yields a set of all the narratives during the Liberation Day episode and the number of articles assigned to each narrative on each day.

The next step is to measure the informational contents of each narrative. I construct *narrative regimes*, which answer the question: how much information about the aggregate price impact of tariffs – and in what direction – does the average article from narrative k contain on day t ?⁵ To do so, I build a proxy for the aggregate price impact of tariffs: the daily return on a long-short portfolio of commodities (à la Fama and French, 1992, 1993), sorted on statutory tariff exposure (Amiti et al., 2019; Fajgelbaum et al., 2020). (Circularity concerns are obviated by the use of commodity prices instead of equity prices in the construction of narrative regimes.) I then decompose the price impact of tariffs across all narratives using a time-varying Total-Variation Regularized Fused LASSO (Rudin et al., 1992; Tibshirani et al., 2005), which yields piecewise-constant narrative regimes on the per-article level. For instance, it becomes possible to quantify the way the price impact of tariffs (on commodities) decreases when market participants learned of two injunctions against tariffs on May 28-29, 2025 (-36 bps from the daily price-impact of tariffs on May 29), and the subsequent increase when the injunctions were stayed, leaving tariffs in place (+27 bps on June 3).

I take each narrative’s implied price impact of tariffs on a particular day (i.e., the product of the per-article narrative regime and the number of articles), to be a *narrative signal*. Regressing daily stock returns on narrative signals using a standard specification with industry-level shrinkage of loadings delivers a narrative-implied price impact for every industry, narrative, and day. For example, on July 31, 2025 – the day after the US-Japan deal set an a 15+% tariff on Japanese auto-sector imports – the narrative on the automotive sector’s adaptation strategies explained 55% of Ford’s return that day (an auto-narrative-attributable 0.94p.p. increase, relative to a 1.7% return), while explaining -7% of the financial firm Fiserv’s return.

I show that narratives outperform standard topic-modeling tools (Blei et al., 2003; Hoffman et al., 2010) prevalent in the literature (see, e.g., Bybee et al., 2024, 2023): tariff narratives explain about 18% of stock returns in the period, 52% higher than the median topic-modeling alternative considered, and 26% higher than the best-performing alternative: a hybrid approach which replicates my narrative regime framework on the basis of topic models, so that the only difference is

⁵I account for the fact that both the informational contents of a narrative and the economic impact of tariffs are likely to be time-varying. By construction, on any given day, the sum across narratives of these per-article beliefs scaled by the number of articles of each narrative estimates the aggregate price impact of tariffs. This belief-elicitation exercise thus also has a natural interpretation as measuring the contemporaneous expectations of tariff price-impact intensity, decomposed across narratives.

the text-analysis technique used.

Because narratives offer a way to analyze structural patterns which organize text and because these structures offer fundamentally different predictions about the future of tariffs, it becomes meaningful to ask whether stocks are sensitive to multiple narratives or a few, whether or not the narratives to which a stock is exposed agree on the asset's price, and whether this matters for financial markets. I therefore build three measures to capture the geometry of stocks' exposure to narratives on the industry-day level. *Total narrative-implied price pressure* aggregates the total magnitudes of price movements implied across all narratives for a given industry-day, and hence describes whether tariff-related narratives matter for the returns of stocks in that industry. *Dispersion* is a measure of the concentration of active narratives (computed via Shannon entropy): it asks whether many or few narratives drive a stock's price on a given industry-day. Dispersion is an inverse measure of concentration and reflects the fragmentation of the industry-day-specific informational environment. It is lowest if all narrative-exerted pressure is driven by a single narrative, and highest when pressure is spread uniformly across narratives.⁶ Finally, *directional disagreement* quantifies the intensity of sign conflict of narratives' impacts on prices by capturing the share of narratives' price-impacts for that industry-day which negate each other.⁷ I define *narrative cacophony* as an interaction term between (i.e., product of) dispersion and directional disagreement, capturing the intuition that interpretation becomes difficult in the presence of many relevant narratives having contradictory pricing implications.⁸

As markets aggregate diffused information through agents' trading, the first logical step is to consider the relationship between narrative cacophony and trading volume. The canonical literature on disagreement in finance (cf, e.g., Harrison and Kreps (1978); Harris and Raviv (1993); Kandel and Pearson (1995)) posits that volume always increases in disagreement. Indeed, in Appendix J, I derive that the workhorse model of Kandel and Pearson (1995) implies that narrative cacophony should have a non-negative effect on trade volume. The empirical evidence, however, points to the opposite; narrative cacophony has a robustly negative association with volume. To show this, I regress volume on narrative dispersion, directional disagreement, cacophony (the interaction of dispersion and disagreement), and a series of control variables, including: total narrative-implied price pressure, the aggregate price impact on commodities, news article volume, absolute returns, lagged trade volume, and measures of uncertainty like VIX, TPU (the

⁶On the average stock-day, dispersion is about 73% of its theoretical and empirical maximal value. Mapped to its perplexity equivalent to represent the "effective number of narratives," this measure means that, on the average stock-day, the discourse has the same narrative dispersion as an environment with about 7.24 perfectly equally-distributed narratives (out of 15 in the sample).

⁷The average value of directional disagreement in the sample is approximately 0.75, meaning that 75% of narrative activity cancels out in its price-pressure implications on the average industry-day. The highly-contentious, complicated nature of the Liberation Day episode confirms that it is a natural laboratory for the study of narratives and disagreement.

⁸Unlike existing measures of disagreement built from analyst forecasts, surveys or social media posts, and sentiment indices, all of these measures are constructed from realized, narrative-attributable daily price impact. To the best of my knowledge, these are the first measures of disagreement to be simultaneously derived from prices and attributable to specific endogenously-recovered thought-patterns investors exhibit.

tariff-specific Economic Policy Uncertainty index variant), and the bid-ask spread.⁹ I find that a joint one-s.d. increase in dispersion and directional disagreement lowers volume by about 5% (1.6 s.d.). I then propose one way to theoretically rationalize these results: I include in the Kandel and Pearson (1995) set-up an ambiguity-aversion-like term, capturing agents' sensitivity to narrative cacophony (in the style of smooth ambiguity Klibanoff et al., 2005), and show that it gives rise to a volume dampening effect if agents are sensitive to narrative cacophony; the model recovers the standard predictions of Kandel and Pearson (1995) if agents are indifferent to cacophony.¹⁰

To confirm that cacophony-suppressed volume is responsible for the low explanatory power of narratives on certain days, I sort stock-days by the share of model-explainable trade volume stifled by narrative cacophony.¹¹ I show that, when volume suppressed by cacophony is high in relative terms, narrative-induced beliefs lose their explanatory power (falling from 25.6% in the lowest-cacophony quartile to 0.5% in the highest-cacophony quartile).¹²

Moreover, in forecasting regressions, I show that when the share of foregone trading is high, prices are slower to incorporate narrative signals: the previous day's narrative signals go from having no effect on the next day's return to a large and significant effect (from a coefficient of 0.02 in the lowest quartile of cacophony-suppressed volume to a coefficient of 0.53 in the highest). This suggests that markets fare increasingly worse at aggregating public information as narrative cacophony overwhelms investors, complicates the interpretation of information, and suppresses volume.

While the paper focuses on financial markets, my analysis also has implications for the analysis of narratives in general. First, narratives endogenously cluster around propositions which make predictions about the future, rather than descriptions of past events. Second, similarity in predictions is driven by similarity in mechanisms ("why" and "how" claims), while similarity in past events is explained by similarity in plot ("who" and "what" claims). Third, the *informativeness* of a narrative regime – the absolute value of its per-article narrative regime coefficient – is inversely related to the coherence of within-narrative predictions: on a given day, narratives whose constituent stories posit more coherent predictions are less informative. This is because absolute homogeneity in predictions of a narrative means there is little more to be learned from the narrative, and hence that the narrative has likely already been priced in its entirety.

⁹These results do not replicate with topic modeling and hybrid approaches. This is plausibly because dispersion among topics (collections of keywords) does not carry the same meaning as dispersion among narratives, which are different enough for their number to already be meaningful.

¹⁰Beyond mathematical expediency, drawing on insights from the ambiguity literature is appealing for two important conceptual reasons. First, the conjecture that ambiguity should dampen trade goes back, at least, to Knight (1921); Keynes (1937); Bewley (1986) and is frequently motivated by the intuition that agents are reluctant to trade when they feel that they do not understand (see also Dow and Werlang (1992) and Epstein and Schneider (2003)). Second, narrative cacophony can be interpreted as a natural aggregate-level analogue to ambiguity: a set of priors is ambiguous only if a decision-maker entertains multiple, behaviorally-different beliefs; similarly, an informational environment is ambiguous if it is characterized by multiple narratives with contradictory pricing implications.

¹¹Considering this share allows me to capture the relative importance of cacophony on a particular industry-day, and to directly ask whether the share of trading attributable to narrative cacophony explains the share of information that remains unincorporated.

¹²The CAPM exhibits a similar pattern (55.1% to 28.6%), as does a mixed CAPM and narrative framework. I also verify that both the R^2 and delayed pricing-in findings cannot be explained by realized volume effects alone.

The paper proceeds as follows. Section 2 provides a literature review. Section 3 develops the hypotheses. Section 4 proposes a theoretical, empirically-implementable definition of narrative, and applies the narrative-extraction methodology to the “Liberation Day” tariff discourse. Section 5 builds piecewise-constant narrative regimes to elicit each narrative’s price-relevant information contents. Section 6 estimates stocks’ narrative loadings based on narrative regimes and constructs measures of within-stock narrative disagreement. Section 7 presents the results on narrative cacophony, volume, and returns. Section 8 concludes.

2 Literature Review

The paper contributes to five strands of literature: (i) information aggregation by markets; (ii) the role of disagreement (especially in explaining trade volume); (iii) modeling narratives; (iv) the text-as-data literature; and (v) a literature on tariffs and associated policy uncertainty.

Information aggregation. That markets aggregate information is a foundational intuition of financial economics (Cowles, 1933; Hayek, 1945; Fama, 1970). Empirically, however, public information explains surprisingly little of the variation in prices (e.g., Roll, 1988; Cutler et al., 1989). The literature has, thus far, posited three main explanations. The first attributes the low R^2 to private information (Morck et al., 2000). The second emphasizes (rational or irrational) investor inattention or the prevalence of noise (Hong and Stein, 1999; Hirshleifer and Teoh, 2003; Cohen et al., 2020). The third argues that explanatory power R^2 is low because conventional measures of public information are insufficiently granular or targeted (Boudoukh et al., 2019). The latter strand also served as the (partial) inspiration for the text-as-data literature which I discuss separately below.

These explanations share a common premise: public information is available to everyone, and the question is whether it reaches prices. On one extreme of this reasoning is a market as envisioned by Hayek (1945), which aggregates fragmented information perfectly; on the other, a market in which public information becomes de facto private information, due to observation, understanding or attention frictions, and is then only partially revealed in prices, à la Grossman and Stiglitz (1980). Where precisely does one land on this spectrum? I propose a new channel, and argue that the answer lies with the interpretability of information.¹³ In my set-up, interpretation can be challenging even when information is fully public and receives full attention. I show, in particular, that the difficulty of interpretation varies across stocks and days, and that this variation explains how well public information is aggregated. I also propose a mechanism by which this happens: in cacophonous narrative environments, information becomes difficult to interpret – precisely because it accommodates a variety of contradictory interpretations – and agents become

¹³My focus on interpretability is motivated by a large literature at the intersection of finance and accounting, which documents the difficulty of interpreting public information (see, e.g., Bloomfield, 2002; Li, 2008; Loughran and McDonald, 2011), as well as by a literature on short-selling which finds that short sellers’ main driver of profit is often their superior ability to interpret public information, rather than access to private information (see, e.g., Engelberg et al., 2012; Boehmer et al., 2020).

more reluctant to trade. The foregone trade volume, in turn, corresponds to decreased explainability of prices.

Disagreement and trade volume. Trade volume and disagreement have received significant attention in the literature. Among the most seminal papers in this literature are Harrison and Kreps (1978); Kim and Verrecchia (1991); Harris and Raviv (1993); Kandel and Pearson (1995); Hong and Stein (2007); Banerjee and Kremer (2010).¹⁴ In general, the theoretical literature often models volume as always increasing in disagreement. Under such frameworks, one can derive that narrative cacophony should have a non-negative effect on trade. I extend these frameworks by decomposing “disagreement with the average belief” into magnitude, dispersion, and directional disagreement, both in a theoretical set-up and in the empirical analysis, and documenting that narrative cacophony – the interaction of dispersion and directional disagreement – should and does have a negative effect, as long as agents are averse to cacophony.

The theoretical rationalization of this finding draws on intuition from the ambiguity literature and goes back at least to Knight (1921), (Keynes, 1937, p. 216) and (Bewley, 1986, p. 269): that within-agent confusion (ambiguity) should drive down trade by inducing a kind of decision-making paralysis. The insight has been formalized in several models, including de Castro and Chateauneuf (2011), Billot et al. (2000), Klibanoff et al. (2005), and Dow and Werlang (1992), the latter deriving an explicit no-trade theorem.¹⁵ This ambiguity-induced paralysis in trading conjecture has proven difficult to test empirically: due to the challenge of eliciting a single agent’s multiple priors and ambiguity attitudes, evidence has necessarily been experimental (see, e.g., Bossaerts et al., 2010). By proposing a model in which agents hold a single narrative belief but can be averse to informational environments in which there seem to be many reasons other investors disagree with them, I am able to test this intuition with field data. In particular, (global) narrative cacophony is a measurable feature of the overall informational environment and the aggregate-level analogue to classical (within-agent) ambiguity.

Moreover, empirical work on disagreement, similar to its theoretical counterpart, typically considers uni-dimensional measures of disagreement, often modeled by a variance of analyst forecasts or sentiment, when studying volume or asset pricing (cf, e.g., Diether et al. (2002); Bamber et al. (1997); Baker and Wurgler (2006); Goldman et al. (2024); Cookson and Niessner (2020)). In addition to evidence of the novel narrative cacophony mechanism, to the best of my knowledge, this paper also provides the first priced, daily, news-derived measures of disagreement.

Modeling Narratives The study of stories and narratives in economics gained popularity with the seminal work of Shiller (2017, 2019). Formalizations have been proposed by Eliaz and Spiegel (2020) and Glazer and Rubinstein (2021) which model stories as Directed Acyclical Graphs (DAGs),

¹⁴Discussion of heterogeneous expectations in speculation and information as a source of trade can be traced back, at least, to Hirshleifer (1975); Feiger (1976). There is also an active literature on disagreement and returns, which explains why disagreement sometimes corresponds to higher and sometimes to lower returns (see, e.g., Diether et al., 2002; Atmaz and Basak, 2018).

¹⁵See also and Epstein and Schneider (2003) and ?.

often with causality¹⁶ and belief-updating, respectively. Focusing on causality, while theoretically elegant, has proven difficult to measure in data, and hence a bit of an empirical straight-jacket. The definition of “story” in this paper can be seen as a minimal simplification of this DAG structure to allow for empirical scalability and implementation.¹⁷

There is also a related applied literature, often reliant on surveys and macroeconomic expectations (see, e.g., Andre et al. (2026); Giglio et al. (2021)). This paper proposes the relaxation of the following approaches common in that literature: that narratives are (i) specified by the researcher ex ante; (ii) studied with beliefs as the outcome variable of interest, not market prices (e.g., surveys can elicit participants’ inflation expectations and which cause of inflation the participant identifies as important, but there is no method currently to link reasoning strategies to market outcomes); and (iii) analyzed individually, without accounting for frictions induced by their multiplicity. I measure narratives endogenously from a corpus of natural texts, elicit for each narrative a price-based belief, and show the multiplicity of narratives does indeed have an effect on how efficiently markets aggregate information.

Text-as-Data The paper seeks to contribute to the literature on text-as-data (Gentzkow et al., 2019) methods. Early work measures sentiment with dictionaries (Tetlock, 2007; Loughran and McDonald, 2011) or counts of keywords (Baker et al., 2016). A second generation of work introduced recurring groups of endogenously-occurring keywords (“topic” models) to extract substance of news and study its association with returns and macroeconomic outcomes (Blei et al., 2003; Hoffman et al., 2010; Hansen et al., 2018; Bybee et al., 2024, 2023). A third operationalizes embeddings and LLMs, including embedding-derived similarity measures (see, e.g., Hanley and Hoberg, 2010; Hoberg and Phillips, 2016; Araci, 2019) and LLM use to deepen understanding of informational contents by (see, e.g., Bybee, 2025; Sarkar, 2026; ?).

In this paper, I leverage LLM and embedding capabilities¹⁸ of the third generation of papers along with some of the intuition from the second generation in order to push beyond narrative substance to narrative structure. In particular, my narrative extraction methodology identifies how information is organized into competing interpretational models which generate predictions about the future, allowing for novel conjectures about narrative cacophony and interpretational complexity. Narrative number, size, and content of narratives all emerge endogenously. A horse-

¹⁶See, for instance, Pearl (2009) and Sloman (2005).

¹⁷In my set-up, stories admit a DAG representation: directed edges imply order, a necessary but not sufficient condition for causality. Moreover, attention is restricted only to directed paths with no branching. Micro-theoretical discussions of narratives also overlap to a considerable extent with the literature on model uncertainty: at its core, following the Marinacci (2015) definition, a model is a probability distribution over [future] states. While a collection of models, each with a probability distribution, is also prohibitively difficult to operationalize empirically, simplifying to stories (which can, equivalently, be written as degenerate distributions over (subsets of) future states) renders the object elicitable from text data with my methodology. In short, the notion of “story” that I propose attempts to draw on deep microtheoretic intuitions already present in the literature, and makes minimal simplifications required for empirical tractability. For models of narratives in other contexts, see Barron and Fries (2024) for a survey.

¹⁸Disciplined by a fully algorithmic, theoretically grounded workflow, and only where semantic understanding is strictly necessary, restricted to minimally-small units of text where, otherwise, human intervention would be required to extract narratives from text without demand effects.

race against topic models shows that the distinction is valuable: pricing and volume results are stronger with narratives than topics. Appendix I discusses in detail the difference between the topic-modeling-substance approach and the narrative structure approach I propose.

Tariffs and Policy Uncertainty Finally, I contribute to a literature on various facets of trade and uncertainty, such as the Baker et al. (2016); Caldara et al. (2020); Manela and Moreira (2017), which were among the first to use text to create proxies of economically-relevant but hard-to-quantify uncertainty using text-measures. As for trade in particular, Bianconi et al. (2021), and Amiti et al. (2019); Fajgelbaum et al. (2020) among others, discuss the economic impacts of tariffs. This paper provides the first account of the role of narratives in the Liberation Day episode, and a way to measure interpretations (narratives) and interpretational complexity (narrative cacophony), which is a concept closely related to but distinct from policy uncertainty.

3 Hypothesis Development

The aim of this paper is to test the classical Hayek (1945) intuition that diffuse information is incorporated into prices via trading by proposing interpretation as a mediating factor. The mechanism proposed in this paper can be visualized as follows:

$$\underbrace{\text{information} \rightarrow \text{trade}}_{\text{interpretation}} \rightarrow \text{prices}.$$

In particular, I posit that (i) information which is difficult to interpret (because it admits many interpretations with contradictory pricing implications, i.e., information which gives rise to a narrative cacophony) leads to lower trade volume. When trade volume is lower because of cacophony, public information (ii) explains a smaller share of returns, and (iii) is incorporated into prices with a delay.

Hypothesis 1. Narrative cacophony decreases trading volume.

Models of disagreement (e.g., Harris and Raviv, 1993; Kandel and Pearson, 1995; Banerjee and Kremer, 2010) typically have trading always increasing in disagreement of agents (who are indexed by j):

$$\mathcal{V} \propto \int |\Delta \text{belief}_j - \Delta \text{avg. belief}| dj.$$

In such models, agents hold one belief, and are confident and dogmatic. Taking the Kandel and Pearson (1995) model as baseline, in Appendix J, I show that such models predict a non-negative cacophony effect.

I next derive one way to introduce a minimal change to the Kandel and Pearson (1995) model which, instead, predicts a negative cacophony effect: I maintain the assumption that agents hold one narrative, but relax the assumption that agents are confident in their dogmatism. More concretely, investors continue to adhere to a single narrative belief (as in the Kandel and Pearson

(1995) set-up) but can express some doubt or discomfort as to whether the presence of other agents' narratives might mean that they are wrong. The more narratives with contradictory pricing implications they observe in the market, the greater agents' discomfort. This discomfort dampens trade by entering investors' demand functions as a kind of additional perceived variance. If, however, agents express no self-doubt and are confident in their dogmatism, the standard set-up of Kandel and Pearson (1995) obtains.

Mathematically, I recover cacophony aversion by incorporating elements of smooth ambiguity of Klibanoff et al. (2005). While there are models in which ambiguity dampens trade (see, e.g., Dow and Werlang, 1992; Epstein and Schneider, 2003; Klibanoff et al., 2005; Maccheroni et al., 2013) – and the conjecture that ambiguity should dampen trade goes back, at least, to Knight (1921); Keynes (1937); Bewley (1986) – these models typically rely on each investor holding multiple beliefs simultaneously and being averse to trading when he or she faces ambiguous beliefs. As multiple priors within a single agent are notoriously difficult to elicit, such models are very hard to test outside a lab setting. By avoiding the stipulation that an agent must hold multiple beliefs simultaneously, I can test this theory with field data. In fact, my model proposes narrative cacophony as a natural aggregate-level (and hence easily observable) analogue to ambiguity: a set of priors is ambiguous only if a decision-maker entertains multiple, behaviorally-different beliefs; similarly, an informational environment is ambiguous if it is characterized by multiple narratives with contradictory pricing implications.

Because narrative cacophony is defined as an interaction of dispersion (an inverse measure of narrative concentration) and directional disagreement (sign conflict of narratives' implications for returns) and the levels of both variables are included as control variables in all analysis, the hypothesized cacophony-dampened volume effect is empirically distinct from plausible alternative explanations. Pure rational inattention should load on dispersion; pure disagreement should load on directional disagreement. That their interaction would have a separate effect cannot be explained by one of the two, or even the two jointly.

The first hypothesis on volume presents the mechanism of what comes next. If cacophony dampens trade and markets incorporate dispersed information via trading, then cacophony-attributable foregone trade captures the extent to which there is information that could have been priced but which was not incorporated.

Hypothesis 2. When volume is low due to cacophony, a smaller share of returns is explainable by narratives and, separately, by CAPM.

The second hypothesis and corresponding set of results quantifies the degree to which cacophony (via foregone trading) affects market pricing. I sort the data by quartiles of the share of tariff-attributable volume which is suppressed due to the cacophony effect. These quartiles capture the relative importance of cacophony-foregone-volume to tariff-related trading. Then, I check whether narrative-signals' explanatory power decreases across quartiles as the importance of cacophony-induced foregone volume increases. Repeating the test with the CAPM market factor confirms that results are not an artifact of some spurious relationship between cacophony and

narrative signals’ noisiness. (The CAPM results are consistent with the intuition of [Savor and Wilson \(2014\)](#), who argue that CAPM works better on days with more macro news: I find that CAPM works better when there are more *easily-interpretable* macro news.)

Passing to the share of tariff-attributable volume suppressed by narrative cacophony is an important feature of the design. The tests do not ask whether confusing news days have worse price discovery. Instead, I ask whether the amount of relevant trading that is prevented by narrative cacophony predicts the amount of information that remains unincorporated in returns. In other words, the share allows me to isolate days on which cacophony is meaningful in a relative sense (e.g., a day on which cacophony-attributable volume loss is low but on which all volume is extremely low is still a day on which cacophony was a meaningful factor).

Hypothesis 3. When volume is low due to cacophony, the market is slower to price information: the previous day’s narratives come to be priced with a delay.

The third hypothesis, on pricing dynamics, presents a useful converse – confirming that markets are less informationally efficient (à la [Fama, 1970](#)) – and tests an additional dimension. As I document a delayed pricing-in effect and show that past narratives become more influential for future returns when cacophony-attributable foregone volume is high, I can rule out the situation in which there is simply less information and more “pure noise” on days with higher shares of trade foregone due to narrative cacophony. Furthermore, while the first two hypotheses can be consistent with a story of cacophony reflecting an increased presence of private information (e.g., investors understanding that there is information which they cannot observe and “grasping at straws” to fill in the gaps by considering more narratives, giving rise to higher cacophony), the third hypothesis cannot be explained by the prevalence of private information alone: it is precisely the public information that is incorporated into prices with a delay.

The finding that lower trade attributable to cacophony is associated with a delayed pricing-in effect can also be interpreted as a microfoundation for the gradual diffusion of information assumption in models of under-reaction like [Hong and Stein \(1999\)](#).

4 Narrative-Extraction Methodology

I develop an empirically-implementable framework for narrative extraction. The methodology proposes theoretical definitions of stories, narratives, and story-similarity, and leverages embeddings, dynamic programming and community-extraction algorithms in order to cluster similar stories, derived from natural texts, into narratives. Narratives are extracted without pre-specifying the themes, contents, sizes, or distinguishing features of narratives, or the number thereof. An LLM is only used for the tasks for which, otherwise, a human subject could be used: specifically, the provision of (structured) summaries of texts. Otherwise, where semantic understanding is necessary, I use fully deterministic embeddings (high-dimensional vector spaces capable of encoding semantic contents).

The methodology’s focus on grouping stories by similarity in story-telling structure is motivated by insights from narratology. Ricoeur (1983) noted that internal substance (a chronicle of events) is transformed into a story by *emplotment* (*mise en intrigue*): the configuration of events into a unified plot that makes them intelligible as pointing toward a consequential future state.¹⁹ Ricoeur also holds emplotment to be the de facto foundation of heterogeneous belief: two agents sharing some of the same events can emplot them into entirely different narratives depending on the causal or interpretational frameworks they employ. A similar distinction is drawn between the notions of *fabula* (the underlying sequence of events) and *syuzhet* (the arrangement of events into coherent narratives) in the foundational narratological work of Tomashevsky (1925). In other words, narratological theory has long distinguished between the events that constitute narrative substance and the particular configuration through which those events acquire their meaning and significance within a larger whole.²⁰ In some sense, this, too, is the difference between topic modeling approaches which are primarily tuned at measuring substance, and this paper, which is more interested in the structures that mold the substance into narratives.

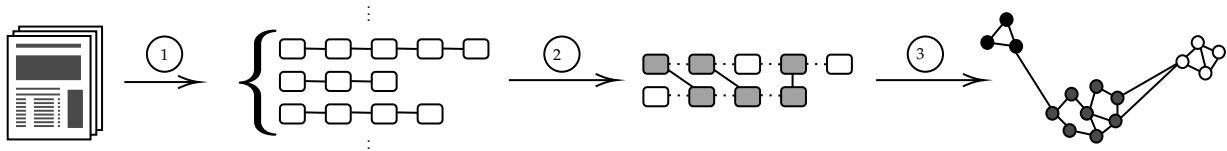


Figure 1: A Methodological Overview.

Narrative extraction proceeds as follows: (1) extract “stories” (lists of facts) from articles (s.4.1); (2) compare all stories (pairwise) by comparing constituent facts (s.4.2); (3) partition the set of stories such that within a block (= “narrative”), stories are similar in meaning but different across blocks (s.4.3).

Figure 1 illustrates the methodology: Step 1 begins with an extraction of stories from a corpus of natural texts; Step 2 quantifies the similarity of every pair of stories; and Step 3 clusters similar stories into narratives. Once the narrative clusters have been obtained, each narrative can be characterized in a tractable, parsimonious way. Step 2, with its novel, implementable conceptualization of story-similarity – which exploits a quality-vs-quantity trade-off in underlying comparisons – contains the bulk of the conceptual innovation of the narrative-extraction methodology.

The following sub-sections presents the methodology, with an emphasis on modeling story-similarity, and its application to the “Liberation Day” episode. An explanation of the methodology in full detail is presented in Appendix 4.

¹⁹Emplotment is the central concept of “The Threefold Mimesis” posited in Ricoeur (1983). The author argues to fully appreciate a narrative one must assess it in its totality: events gain meaning from their place in the whole.

²⁰It is from this observation that hypotheses regarding the pivotal role of predictions within a narrative are derived: it is natural to expect, for structural narratives, predictions to play a more defining role in structuring narratives than realized events, and for a narrative’s potency to be related to the concordance of these predictions.

4.1 Stories: Definition and Extraction

A *story* is list of *statements*, in the order in which they happen. A shopping list or a list of grievances is not a story. Neither is a substance-less collection of timestamps. Something has to happen, and there has to be an order in which facts unfold (even if a trivial one). A *narrative*, in turn, is a cluster of stories *similar in meaning*, a notion to which section 4.2 is devoted.

Definition 4.1. Let $\mathcal{F}$ be the set of statements, where each $f \in \mathcal{F}$ is a statement, which describes something which happens at some moment in time.

Definition 4.2. A *story* is a (finite) list of statements in chronological order.

A story can be composed of realized statements and hypothesized future statements, for which the natural terms would be “events” and “predictions,” respectively. Depending on the timing, the predictions of one story may be the realized events of another, so the overall narrative-extraction methodology does not separate by statement-type, which is instead analyzed separately in Appendix K.

Definition 4.3. The *set of all possible stories* is the set of all finite tuples whose elements are statements:

$$\mathcal{Q} = \bigcup_{n \geq 1} \mathcal{F}^n,$$

and a story is an element thereof.

Implementation To extract stories (i.e., to summarize news articles into a list of chronologically-ordered statements) I submit each article to an LLM (Claude Sonnet 4.5 timestamped to 2025-09-29 and with temperature [stochasticity] set to zero for maximal replicability; in memory-less, independent fashion, à la i.i.d. draws, with the prompt and full implementation details provided in Appendix B.1.1).²¹ The LLM positions statements to reflect the chronological order implied by the article about the real world, irrespective of whether the article recounts events linearly. The LLM is also instructed to extract, for each statement, its projection onto who-what-where-when-why-how sub-statements (see Appendix K for an analysis of story structure based on these features).

Definition 4.4. A *narrative* is a cluster of stories *similar in meaning*.

That is, to obtain the set of narratives, one must partition the set of stories into blocks similar in meaning to each other. Story comparisons should preserve internal chronological order,²² but still

²¹One can readily imagine alternative sources: (ordered) responses to open-ended decision-questions posed in an experiment or survey, testimony or speech transcripts, earnings calls, reports, social media posts, and so forth.

²²Chronological order is an important and immutable characteristic of a story. Order reversal can lead to a story with otherwise identical constituent statements having opposite interpretations, or reversing causality or implications. Consider, for instance, the story (“Country A attacked Country B.” ; “Country B attacked Country A.”) compared to the story (“Country B attacked Country A.” ; “Country A attacked Country B.”). Similarly, it is critical to know whether a drop in inflation predates or follows an interest rate hike by a central bank, whether an investor sells before

allow for some flexibility. The scoring rule should be flexible enough to recognize as quite similar stories which are identical except one has an extra detail but strict enough that too many divergent details make the stories dissimilar. The rule must also be flexible enough to accommodate stories of different lengths.²³

4.2 Story similarity

The methodology exploits story structure and reduces story comparisons to a comparison of constituent statements. There are two questions that must be addressed: given two statements, how should they be compared? and how do we know which statements to compare in the first place? I propose a notion of “optimal alignment”, which optimizes the trade-off between compared statements’ match-quality and quantity.

4.2.1 Statement comparison: how do we compare two statements?

A pair-wise similarity function compares statements:

$$s : \mathcal{F} \times \mathcal{F} \rightarrow [-1, 1],$$

where, for any $A, B \in \mathcal{F}$, $s(A, \emptyset) = 0$ and $s(A, B) = s(B, A)$, and monotone in meaning, with 0 denoting orthogonality and 1 and -1 corresponding to identical or identically opposite meanings, respectively. This similarity function emerges from an axiomatization in Appendix B.2.5, which also discusses the properties of the function, and has a number of interpretations, discussed in Appendix B.2.1. Importantly, that the similarity of a pair of statements can and should be evaluated separately from all others is a consequence of the axiomatization. The preferred interpretation, given the empirical application and the implementation strategy, is of a consensus similarity imputed as a population-assessed similarity average.

Implementation I use OpenAI’s text-embedding-3-large model, combined with cosine similarity, as the similarity function (cf, e.g., Hanley and Hoberg, 2010; Hoberg and Phillips, 2016).²⁴ Embeddings are vector representations of text in which each statement (a single sentence) is mapped

or after stock prices grow, and whether forecasts anticipate or react to economic outcomes. In many cases such as these, “objective” timing can be difficult to ascertain: prices move up and down continuously; to which infinitesimal price change was the investor responding? But it is the subjective timing perceived by a decision-maker that informs his or her decision, and this project aims more to compare reasoning strategies and statements or chronologies deemed salient by decision-makers, than it does to elicit an objective chronology of all statements.

²³Chronological order matters; precise timing does not. I do not insist that time be discrete and that something happen at every period. As a result of this flexibility, it is not obvious which statements we should compare when comparing two stories. (If there were a prespecified timeline, it would, perhaps, be natural to insist on comparing statements unfolding at time t to each other, for each t ; in the absence of such a timeline, the decision of which events to compare is non-trivial and requires explicit modeling.)

²⁴As with the choice of LLM, the methodology allows for the similarity function to be easily swapped out for another. For instance, for alternative implementations, users may have at their disposal human subjects’ responses.

into a high-dimensional vector space and the angle between them measures semantic similarity:

$$s(A, B) = \cos(\theta_{A,B}) = \frac{A \cdot B}{\|A\| \|B\|} \in [-1, 1]$$

for sentences A, B . The function satisfies the desiderata stated above.

In Appendix A, I present a horse-race simulation which shows that the text-embedding-3-large model performs better than alternative embeddings and bag-of-words methods in a neutral database of sentence-pairs benchmarked against human-scored similarity. In Appendix B.2.2, I also discuss the use of a configurable “dead zone” to correct for spurious semantic overlap as obtaining a raw zero cosine-similarity score when working with a data set with shared “technical” jargon is nearly impossible, and these “false similarities” (i.e., scores inflated due to shared context but not shared meaning) pollute the data.

4.2.2 Story comparisons: how do we know which statements to compare?

Story comparisons rely on an aggregation of the pairwise comparison of constituent statements via the above similarity function. Now, the problem is choosing the appropriate statement-pairs to compare. The comparisons must respect chronological order,²⁵ but it is not obvious how flexible one should be on timing, especially in the absence of an objective chronology or discrete time. Consider, for instance, two stories, identical except that one has an additional statement somewhere in the middle. It often makes sense to be forgiving of the inclusion of one extra relatively-insignificant detail, and to say that, all else equal, these stories should probably be quite similar. But if the stories’ middles differ by multiple statements, at some point, one starts to have the intuition that the stories are quite different after all. Moreover, a failure to match on a statement in the middle is more problematic than an omitted statement at the very beginning or the end of a story – the latter being plausibly indicative of different start- or end-points than substantive disagreement.

Figure 2 presents several ways to formalize this intuition. *String* and *sequence* comparisons derive their name from the respective classes in computer science, and evoke the mutability or lack thereof of each object (in some languages). In a *string* comparison, all statement comparisons must be contiguous, and possible comparisons differ only by start-point. In a *sequence* comparison, spacing is infinitely flexible (as long as the original chronological order is preserved). *Strequence* comparisons represent a compromise between the two: they allow for flexible matching, but penalize tenuous choices (i.e., foregone internal matches). The “density penalty” creates a trade-off in the quantity of (non-trivial) matches and their quality: foregoing a contiguous match is optimal only if it facilitates a sufficiently higher-score match as to offset the global penalty.

In order to formally model a comparison of two stories, a few auxiliary notions are required.

²⁵Recall the example of (“Country A attacked Country B.” ; “Country B attacked Country A.”) compared to (“Country B attacked Country A.” ; “Country A attacked Country B.”) These stories should be credited *either* for agreeing on A attacked B, *or* for agreeing on B attacked A, but certainly not both: the order of who attacked whom is crucial to understanding the war, and likely has behavioral and moral implications.

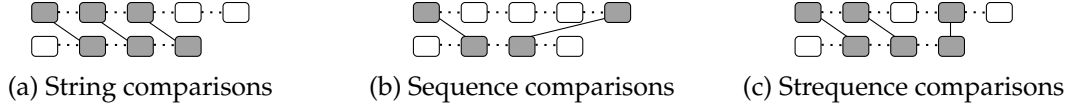


Figure 2: Story Comparison Methods

A summary of the string, sequence, and strequence comparison methods. String comparisons are least flexible; sequence comparisons are most flexible; and strequence comparisons lie in-between, allowing for skipped matches but subject to a match quantity-quality trade-off.

Definition 4.5. A story $(f'_1, \dots, f'_m)$ is an *extension* of a story $(f_1, \dots, f_n)$ if there exists a strictly increasing (hence injective) function $g : \{1, \dots, n\} \rightarrow \{1, \dots, m\}$ necessarily with $n \leq m$ such that $f'_{g(i)} = f_i$ and $f'_k = \emptyset$ (an empty statement) for any $k \notin g(\{1, \dots, n\})$.

Definition 4.6. An *alignment* $j(q_1, q_2)$ of the stories q_1, q_2 is a pair of extensions of q_1, q_2 of the same length. Denote by $\text{len}(j(q_1, q_2))$ the length of stories q_1, q_2 under the alignment j , and by $\mathcal{J}(q_1, q_2)$ the set of all possible alignments of q_1, q_2 . Finally, $j(q_1, q_2)_i$ will denote the pair of statements in the i^{th} component of the alignment.

Alignments allow for story comparisons to be written as the comparison of statements in each position (where extensions and the inclusion of empty statements afford the required flexibility in the statements being considered).

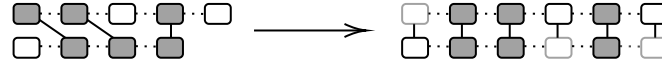


Figure 3: Alignment-based Story Comparisons

The comparison of two stories reduces to the comparison of constituent statements at each position, and alignments allow for flexibility in which statements are placed in which positions, subject to the maintenance of original chronological order.

Now, the full representation for strequence story comparisons can be written as:

$$\begin{aligned}
 V_\alpha(q_1, q_2) &= \max_{\text{all possible alignments } j} \left\{ \underbrace{S_j(q_1, q_2)}_{\text{axiomatized alignment score}} \times (\text{density penalty})^\alpha \right\} \\
 &= \max_{j(q_1, q_2) \in \mathcal{J}(q_1, q_2)} \left\{ \left[\sum_{i=1}^{\text{len}(j(q_1, q_2))} s(j(q_1, q_2)_i) \right] \times \left(\frac{\# \text{ matches}}{\# \text{ matches} + \# \text{ internal empty matches}} \right)^\alpha \right\} \\
 &= \max_{j(q_1, q_2) \in \mathcal{J}(q_1, q_2)} \left\{ \left[\sum_{i=1}^{\text{len}(j(q_1, q_2))} s(j(q_1, q_2)_i) \right] \times \left(\frac{\# \text{supp}(j(q_1, q_2))}{\# \text{supp}(j(q_1, q_2)) + \text{padding}(j(q_1, q_2))} \right)^\alpha \right\}
 \end{aligned}$$

where $\alpha \geq 0$ determines the severity with which tenuous alignments (foregone internal matches) are penalized, and padding counts the number of *internal* empty matches added to

an alignment:

$$\begin{aligned} \text{padding}(j(q_1, q_2)) = & (\max\{i : j_1(q_1, q_2)_i \neq \emptyset\} - \min\{i : j_1(q_1, q_2)_i \neq \emptyset\} + 1) - \text{len}(q_1) \\ & + (\max\{i : j_2(q_1, q_2)_i \neq \emptyset\} - \min\{i : j_2(q_1, q_2)_i \neq \emptyset\} + 1) - \text{len}(q_2) \end{aligned}$$

for alignment $j(q_1, q_2)$ induced by the pair of extensions j_1, j_2 such that $j(q_1, q_2) = (j_1(q_1), j_2(q_2))$. The idea is to penalize only foregone matches between the first and last successful match: outside these, foregone matches are plausibly attributable to different start- or end-points of stories, rather than genuine disagreement about the details.

Remark. The representation built for strequence alignments subsumes both string and sequence comparisons: $\alpha = 0$ corresponds to the “sequence” comparisons case; and $\alpha \rightarrow +\infty$ recovers “string” comparisons.

Finally, the $\max$ operator captures the intuition that cognitive effort is required to find the “right” way to compare stories: two stories are similar if there exists a natural way to align them that reveals high similarity. Any pair of stories can produce a 0– similarity score, but not any pair can obtain a strictly positive one. Other operators – such as $\min$, sum , or averages – are less desirable here because it is always possible to dismiss a comparison of two stories as meaningless by reducing to trivial or “wrong” matches, and because there are many more “wrong” matches than the “right” match.²⁶

Axiomatization I axiomatize the alignment score $S_j(q_1, q_2)$ in Appendix B.2.5. The argument is based on Rusonik  Samuelson  Gilboa (2026), which axiomatizes independent, linear aggregation in a position-based framework (albeit in a different context).

Implementation A full construction of all alignments and then the selection of the optimal alignment would be combinatorially explosive and infeasible with a dataset of non-trivial size. I achieve exactly the same outcome without incurring the computational costs by leveraging dynamic programming (DP). For two stories of lengths m and n I build an $m \times n$ matrix whose entries are pre-computed cosine similarities between corresponding statements, then recover an optimal alignment by dynamic programming in $O(mn)$ (polynomial) time. The DP algorithm maximizes cumulative similarity under a three-way recurrence: match the current statements, skip a statement on the first story, or skip on the second story. Terminal states of the DP algorithm are determined by the positions of first and last statements of both stories, and the number of matches. These positions and number of matches are exactly the information required to calculate the density penalty, governed by the parameter α , which is then applied to each of the retained raw scores in the final optimization step. The algorithm returns the “winning” terminal state by selecting the highest raw score $\times$ alignment-specific density penalty product.

²⁶For a discussion of how zero-similarity matches are treated in the optimal alignment algorithm to avoid spurious matches, see Appendix B.2.2.

The α is configurable and its severity is left to the discretion of the analyst, so as to be flexible enough to accommodate different contexts. In Appendix B.2.3, I propose a selection criterion for α , arguing that a “skip” of a statement must be warranted based on the overall score increase it provides. Robustness to alternative choices of α is discussed in Appendix B.2.4.

4.3 Narrative clustering

Is a given similarity score, say 1.37, of a pair of stories high or low? Is the failure to match on a particular statement a meaningful indicator of dissimilarity? The answers depend, among a host of other factors, on the length of the stories and on the scores other story-pairs (of similar length) received. This motivates the need for relative assessment of similarity. That is, the algorithm should cluster stories into narratives not according to a fixed numerical threshold, but based on whether the stories are more similar to each other than to other stories, conditioning first on length.

Binning stories by optimal alignment length, I standardize the alignment scores. Only the top 2% of edges²⁷ with scores with z-score above 1.28 are plotted.²⁸ With these scores interpretable as measures of exceptional similarity of story-pairs (relative to all other story-pairs of the same optimal alignment length), I construct a graph, where each story becomes a vertex, and each edge denotes a comparison, weighted by the standardized similarity score associated to the pair. In order to extract communities, it is enough to “drop” the edges that are least important, and, in so doing, to create a partition.



Figure 4: Narrative Clustering

Narrative clusters are from a graph whose vertices are stories and edges are weighted by standardized comparison scores. The Leiden clusters stories into narratives by asking which edges should be dropped to recover “well-behaved” (modularity-optimizing) way.

The partitioning is performed by the state-of-the-art Leiden community detection algorithm (Traag et al., 2019), which maximizes “modularity”²⁹ – a common measure of cluster quality,

²⁷As usual, the thresholds are configurable; robustness to choice of threshold for the selected application is shown in Appendix B.3.1.

²⁸Cantelli’s inequality guarantees that the retained scores are in the top 40% of distribution.

²⁹Standard Newman-Girvan modularity maximizes

$$Q = \frac{1}{2m} \sum_{i,j} \left[w_{ij} - \frac{s_i s_j}{2m} \right] \delta(c_i, c_j),$$

where w_{ij} is the edge weight between nodes i, j ; $s_i = \sum_j w_{ij}$ is the weighted degree of node i ; $2m = \sum_{i,j} w_{ij} = \sum_i s_i$ is the total weight of all edges (counted twice); and $\delta(c_i, c_j) = 1$ if nodes i, j are in the same community c , 0 otherwise. The Leiden algorithm simultaneously chooses node-community assignment and the number of communities to maximize Q . Intuitively, for each pair of nodes in the same community, the Leiden algorithm compares the actual w_{ij} to the null model expectation $\frac{s_i s_j}{2m}$ (i.e., the counterfactual under which edges were placed at random proportional to

which considers the density of edges within communities compared to those between communities – and guarantees well-connected clusters. Importantly, Leiden has no pre-set number of communities or community sizes. Furthermore, unlike alternative methods, the Leiden algorithm is not susceptible to stopping at suboptimal local maxima and is fully deterministic (and hence reproducible).

4.4 Extracting Narratives from “Liberation Day”

The Liberation Day Episode The “Liberation Day” tariff episode refers to the shift in US trade policy initiated by President Trump under the International Emergency Economic Powers Act (IEEPA). Citing large trade deficits and a declining domestic manufacturing base, the administration announced sweeping reciprocal tariffs targeting major US trading partners. During the episode, US tariff experienced the largest increase since the 1930 Smoot-Hawley era.³⁰ Discourse at the time reflected the uncertainty pertaining to consequences for global supply chains, financial markets, and negotiations among trade partners.

A short timeline of the episode:

- April 2, 2025 (“Liberation Day”): President Trump declares “Liberation Day” and issues an Executive Order imposing a 10% baseline tariff on nearly all imports, alongside higher, country-specific tariffs for various trading partners.
- April 5-9, 2025: The baseline 10% tariff takes effect on April 5, followed by initial country-specific tariffs on April 9.
- April 9-10, 2025 (The 90-Day Pause): Amid market volatility, the administration pauses the higher reciprocal tariffs for 90 days to open bilateral trade negotiations, leaving the 10% baseline intact.
- July 31, 2025: As the 90-day pause expires, the White House issues updated Executive Orders finalizing revised reciprocal tariff rates effective early August. An executive order concerning the EU was signed on this day, following some negotiations on the 27th, and the terms would be formally ratified into a trade deal on August 21st.³¹

Data: Newspaper Articles I obtain the full dataset of English-language news articles on Dow Jones Factiva from April 1st–July 31st, 2025, tagged as relating to “Trade Barriers/Restrictions,”³² from all authors, on all industries and companies, concerning the United States, Canada, Europe, Asia, and the Asia Pacific, from “major new and business sources” from the United States, Canada, Europe, and Asia. In total, there were 21 973 news articles (over 5000 from US sources; over 6000 from the EU; and over 8000 from Asia). I retain only the unique articles (to eliminate republishings of the same article in another newspaper or its own online affiliate), run the first step of the narrative-extraction methodology and obtain 21 771 stories. 80% of timestamped articles

node strengths). So $Q \in [-1, 1]$, with higher values indicating stronger community structure.

³⁰See, e.g., <https://cepr.org/voxeu/columns/tariffs-dollar-and-equities-high-frequency-evidence-liberation-day-announcement>

³¹See <https://www.congress.gov/crs-product/IF13107>

³²I query Factiva using its structured metadata filters rather than a free-text keyword restriction: the Text field is left blank, the Subject filter is set to Trade Barriers/Restrictions.

each day are written before market open or during market hours of the NYSE, which motivates the same-day pricing-in analysis.³³

There are 869 non-singleton narrative clusters, which cover 15 974 news articles, and the remaining 5 797 stories are assigned to singleton narrative clusters (visualization presented in Figure B.9.). Figure 5 plots each of the top 14 narratives by aggregate size (plus a fifteenth cluster which is a miscellaneous category, pooling the remaining articles) by articles' publication dates. Throughout the empirical analysis, I work with these 14+1 because the top-14 cover more than 50% of all published articles while remaining few enough in number that analysis is tractable and quantitative models are not over-specified.

Narratives' size, emergence, and dissipation are consistent with the periods over which one would expect the narratives to be salient. The narrative-clustering process, therefore, identifies meaningful patterns. For instance, the largest narrative overall – “Global Market Meltdown and Escalating US-China Tariff War” (dark blue) – emerges very quickly, and then begins to shrink in prominence, as general panic over an imminent recession or market crash subsides. The narrative on “Constitutional Challenge to Presidential Tariff Authority” (magenta) appears in late May with the first court rulings concerning the President's authority to impose tariffs, and vanished by mid-June when temporary stays were granted, allowing the Federal Government to prepare its appeals.

While Figure 5 displays only narrative titles, full characterizations of the underlying narratives – including “defining” stories (selected for their eigenvector centrality or coverage), key events and predictions, and an AI summary of each narrative – are presented in C. (Selection criteria and the summary-drafting AI prompt are also included in C.) For comparison, I include also the “topics” (collections of endogenously-recovered keywords) that a leading topic-modeling algorithm produces on the same set of news articles (Table I.2). Unlike narratives, these are much harder to interpret: not every topic has an obvious theme; coherent implications are rarer still.³⁴

The economics of stories' and narratives' structure. In Appendix K, I show that narratives and stories have a meaningful structure. Splitting stories' statements into those which bear on past events and those on future predictions, I show that narratives endogenously cluster around future predictions. Moreover, further decomposing each statement into its who-what-where-when-why-how dimensions, I document that the “plot” dimensions (who, what) drive similarity in past events while “mechanism” dimensions (why, how) are salient for prediction similarity. The construction, implications, and further interpretations are discussed in Appendix K.

³³For the article timestamp distributions, see Appendix B.6. I pool all articles together and set the density penalty to $\alpha = 0.1$, as per the proposed selection criterion. Implementation details and robustness to perturbations is contained in Appendix B.

³⁴e.g., One of the more coherent topics seems to bear on financial institutions: it identifies keywords like “banks”, “loans”, “financial intermediaries”, and so forth. But what exactly the narrative says about financial institutions – and whether constituent news articles are consistent in their assessment of the relationship between institutions and tariffs, or whether they merely share the same keywords – is not obvious.

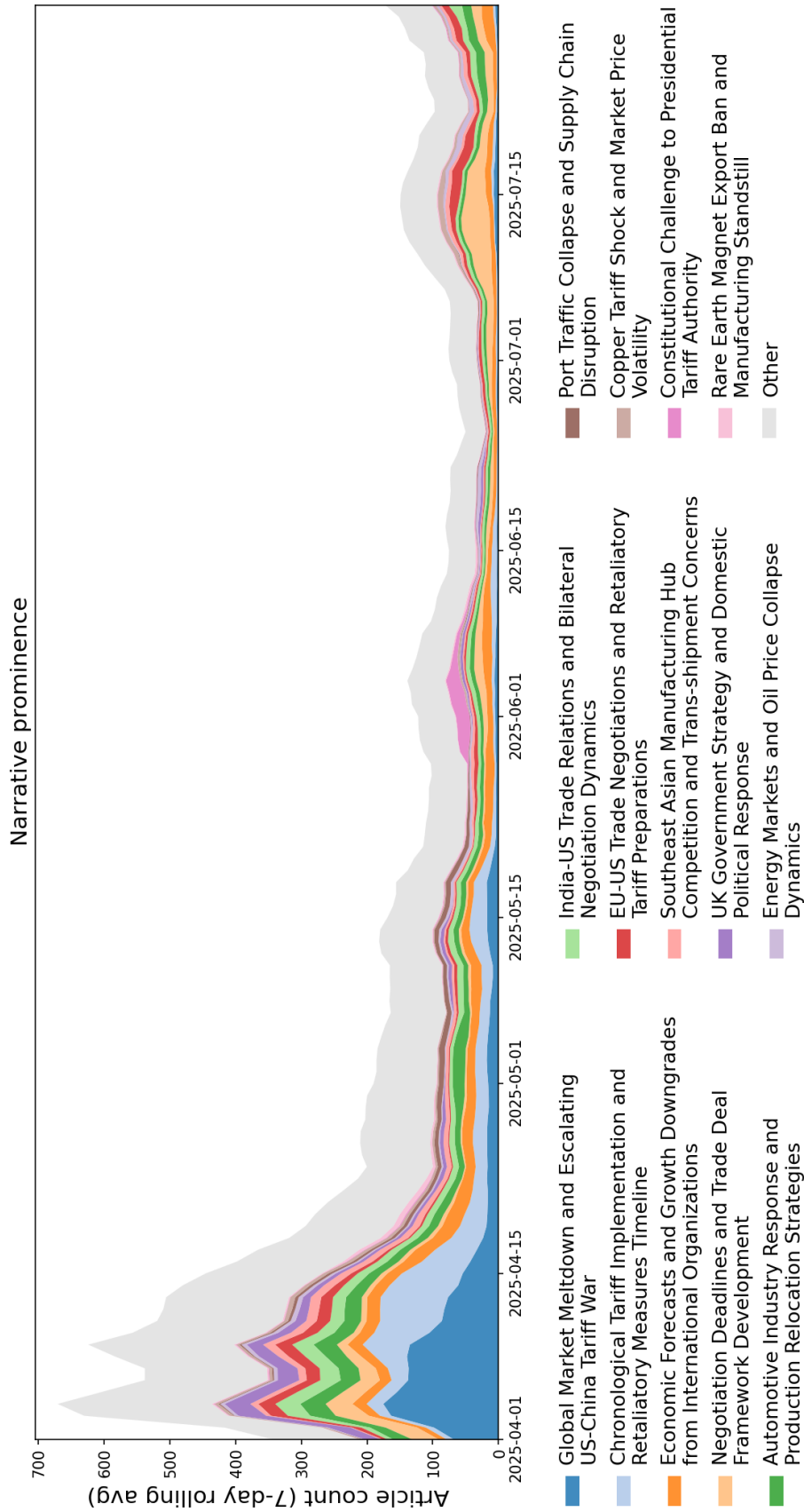


Figure 5: Narratives Over Time

Each of the 14 largest overall tariff narratives is presented in the graph; the remaining narratives are grouped together into a catch-all “other” narrative. Only narrative titles are shown; for a full characterization of each narrative, see Appendix C.

5 Narrative Informativeness & Narrative Regimes

From the narrative-extraction methodology, I obtain the narratives and their size (article count) on each day. But this does not yet tell us anything about narratives’ price-relevant information contents. The next step asks: what information does narrative k contain about tariffs’ price impacts on day t ? I construct *narrative regimes* to which answer this question. The intuition is the following: on each day, each narrative k emits some signals (articles), which comprise that day’s total *narrative k signal*. These narrative signals will be used in section 6 to price equity returns; in this section, I estimate the average per-article *narrative regime* from data such that:

$$\text{price impact of tariffs} \approx \sum_k \underbrace{\overbrace{\text{narrative regime}_{kt}}^{\text{narrative signal}_{kt}}}_{\text{avg. per-article signal}_{kt}} \times \text{number of articles}_{kt}$$

To do so, two ingredients are required: a measure of tariffs’ impacts on prices, and a way to estimate its decomposition across narratives. I measure the aggregate price-impact of tariffs by a long-short portfolio of tariff-exposed commodities, sorted by their statutory tariff exposure (following [Amiti et al., 2019](#); [Fajgelbaum et al., 2020](#)) and re-sorted daily – which, by construction, isolates tariff-attributable changes in commodity prices (in the style of [Fama and French, 1992, 1993](#)). Commodities are a natural choice as they are often the first-order target of tariffs, are – by virtue of being raw inputs – less exposed to compounding higher-order effects of tariffs in supply chains. Importantly, as commodities are not themselves equities, this helps mitigate mechanical circularity concerns when narrative regimes are used to analyze stock prices.

I then estimate a decomposition of this “price of tariffs” across contemporaneous narrative activity, day by day. The time-varying per-news-article correspondence between a narrative and the price of tariffs is the desired *narrative regime*. The central empirical challenge to eliciting narrative regimes is to incorporate sufficient flexibility to allow for time-varying effects,³⁵ but enough rigidity that the model is not over-specified and that the estimation recovers patterns interpretable as meaningful “regimes”.

I elicit these piecewise-constant narrative regimes using the fused total-regularization penalty LASSO introduced by [Rudin et al. \(1992\)](#) and [Tibshirani et al. \(2005\)](#). Where a standard LASSO collapses coefficients towards zero, this model collapses coefficients a constant OLS: that is, it allows for an occasional jump in coefficient only if the change in coefficient corresponds to a sufficiently meaningful increase in the goodness of fit of the whole model (just as the standard LASSO allows for a non-zero coefficient only if it corresponds to a sufficiently meaningful increase in the

³⁵Indeed, there is no reason to assume that narrative informativeness must remain constant over time. Moreover, it is possible that the supply of narratives (from journalists) not be a good indicator of demand (by market participants): a narrative can attract journalistic attention, but – for instance, because these developments were already anticipated by the market, or simply orthogonal to market considerations – to elicit no reaction despite extensive news coverage. The opposite scenario, in which a niche matter is of little appeal to most newspapers but of high importance in a particular economic sector, is also possible. In general, it is natural for the informativeness of narratives to change over time: tariff-related narratives are surely more relevant during the Liberation Day episode than during the 2008 financial crisis. Thus it is imperative to incorporate time-variation in the elicitation of narrative informativeness.

goodness of fit of the model).

Motivation of piecewise-constant narrative regimes It makes sense to model narratives as be episodic or regime-like, motivating a piecewise-constant approach. The piecewise-constant set-up is in the spirit of Markov regimes (Hamilton, 1989). It is natural to expect a particular economic framing – such as “Port Traffic Collapse and Supply Chain Disruptions” – to be relevant to financial markets for a period and to then be displaced by other narratives. In the language of Kuhn (1996), narratives may also be understood as paradigms that appreciate or depreciate in credibility through discontinuous shifts rather than gradual infinitesimal changes. Thus, the market’s sensitivity to a given narrative is expected to change discretely at critical moments.

In a technical sense, piecewise-constant regimes also constitute the minimal relaxation of the constant-informativeness assumption. They introduce only the flexibility needed to capture genuine regime turnover while remaining sufficiently constrained that the hypothesis of discrete regime turnover can be supported or rejected by the data. In other words, piecewise-constant regimes offer the least flexible specification capable of accommodating economically meaningful changes in narrative relevance – and of refuting a null hypothesis of constancy.

Interpretation of narrative regimes Narrative regimes can be interpreted as a contemporaneous expectation- or belief-elicitation exercise which decomposes the changes in a Fama-French-style tariff-impact-isolating portfolio across the salient dimensions identified by narratives. These narrative regimes allow us to understand which narratives informed the market’s expectations of tariff price impacts on a particular day, and how influential the average new article was in that regard.³⁶

I construct the “price of tariffs” in s. 5.1, decompose it across narratives into narrative regimes in s. 5.2, and analyze the structural determinants of narrative regime intensity in Appendix K.4.

5.1 Data: Building Measures of Tariff Exposure and the Price of Tariffs

5.1.1 Structural Industry-Level Tariff Exposure

I construct a measure of structural (statutory) tariff exposure of commodities in the US using the US tariff schedule, and trade and production data. Following Fajgelbaum et al. (2020) and Amiti et al. (2019), I define tariff exposure for good g on day t as the effective tariff rate weighted by the import penetration share, and extend the measure to Liberation Day data:

³⁶This section makes no claim of causal identification. Tariff narratives are equilibrium objects, determined jointly with the price-impacts of tariffs. It is also possible for narratives to sometimes be the cause of economic impact (e.g., by changing agents’ beliefs or serving as coordination devices) and sometimes only the ex-post rationalizations thereof. A further complication for any causality claim is the fact that the same underlying variables – statutory changes, negotiations, surprise shocks – can simultaneously modulate the effect of tariffs on the economy *and* cause news articles to be written. Pinning down a narrative’s informativeness allows us to perform a belief-elicitation exercise and say that market participants are behaving “as if” they are responding to a narrative signal, while avoiding causal attribution.

$$\text{tariff exposure for good } g \text{ at time } t = \frac{\sum_c \text{tariff-rate for good } g \text{ imported from country } c \text{ in } t \times \text{imports of } g \text{ from } c \text{ in } t}{\text{US production of } g \text{ in } t - \text{US exports of } g \text{ in } t + \text{total imports of } g \text{ in } t}$$

where total imports is the sum of country-specific imports across all countries which send good g to the US. The absorption rate (i.e., the denominator) accounts for the relative importance of foreign goods in US domestic markets.

Daily within-month changes in tariff exposure are a function only of changes in trade policy: tariff regime levels, which vary within-month, are obtained from the Harmonized Tariff Schedule provided by the United States International Trade Commission; meanwhile, all import, export, and production data are available from the USA Census Bureau only on the monthly level. The detailed construction of this statutory tariff exposure at the HS6 product-code level is provided in Appendix D.1.

5.1.2 Long–Short Portfolio and the Price of Tariffs

Portfolio construction On each trading day t , all 5,460 HS6 codes are ranked by their exposure. The long leg consists of the top 30% by exposure (codes most heavily taxed relative to their absorption); the short leg consists of the bottom 30%. The top/bottom-30% percentile thresholds are recomputed daily, so the composition of each leg shifts whenever a tariff revision alters the cross-sectional ranking. I restrict to commodities as the cleanest distillation and lowest-tier good in any supply chain. In keeping with the Fama and French (1992, 1993) style of long-short portfolio construction, I assign each HS6 code in each portfolio leg the same weight.

Commodity price data For each of the 5,460 HS6 codes in the exposure panel, I source daily commodity spot prices from a variety of sources to obtain a price. The full construction is described in detail in Appendix 5.1.1. I restrict the portfolio construction to commodities having US spots and futures.³⁷ Following Fama and French (1992, 1993) and Jegadeesh and Titman (1993), I maintain the ex-ante sorting rule and do not re-fill the portfolios after excluding commodities with unusable prices to avoid endogenous selection and contamination by “middle values.” The resulting portfolios have an average of 25 long and 23 short unique commodities in each leg, and are very stable over time.³⁸

Factor return The simple daily return for commodity s is $\Delta p_{s,t} = (p_{s,t} - p_{s,t-1})/p_{s,t-1}$, always taking the end-of-day closing prices. The factor return on day t is the equally weighted long-leg

³⁷Lower-frequency prices introduce noise, and foreign commodity prices are a poor proxy for American prices responding to American import tariffs.

³⁸Because many HS6 codes within a chapter share the same underlying price series (e.g. all flat-rolled steel products map to the HRC futures contract), the effective number of independent price signals per leg is smaller than the raw HS6 count.

average minus the equally-weighted short-leg average:

$$\Delta P_t = \overline{\Delta p}_t^{\text{long}} - \overline{\Delta p}_t^{\text{short}}.$$

Figure D.2 summarizes the behavior of the “price of tariffs” portfolio. The long and short legs meaningfully diverge as the tariff regime intensifies and, at its height, the factor accumulates an approximately 2% cumulative return over the window, consistent with high-tariff-exposure commodities bearing greater price pressure than lower-exposure ones.³⁹ This is broadly on the order of similar estimates in historical periods of high tariff uncertainty.⁴⁰

5.2 Building Piecewise-Constant Narrative Regimes from the Price of Tariffs

Let $\mathbf{x}_t = (x_{1,t}, \dots, x_{K,t})^\top$ be the vector of standardised article counts, where $x_{k,t} = (n_{k,t} - \bar{n}_k)/\sigma_k$ and $\bar{n}_k$, σ_k are the full-sample mean and standard deviation of narrative k , and $n_{k,t}$ is the backwards-looking seven-day rolling average (for smoothness).⁴¹ I model the tariff price factor log-return as

$$\Delta P_t = \overline{\Delta p}_t^{\text{long}} - \overline{\Delta p}_t^{\text{short}} = \alpha_t + \mathbf{x}_t^\top \boldsymbol{\beta}_t^{\text{std}} + \varepsilon_t, \quad t = 1, \dots, T, \quad (1)$$

where α_t is a time-varying intercept and $\boldsymbol{\beta}_t^{\text{std}}$ is a K -dimensional time-varying coefficient vector. The goal is to allow $\beta_{k,t}^{\text{std}}$ to be time-varying, but in a constrained way, consistent with the intuition that narratives ought to have “regimes” in which they are active – that is, each $\beta_{k,t}^{\text{std}}$ should be piece-wise constant in t , with a modest number of jumps justified by significantly different “regimes” in the data. These paths are estimated via a pure fused LASSO:

$$\min_{\boldsymbol{\beta}_t^{\text{std}}} \sum_{t=1}^T \|\Delta P_t - \alpha_t - \mathbf{x}_t^\top \boldsymbol{\beta}_t^{\text{std}}\|_2 + \lambda_{\text{tv}} \sum_{t=2}^T \sum_{k=0}^K \|\beta_{k,t}^{\text{std}} - \beta_{k,t-1}^{\text{std}}\|_1, \quad (2)$$

with $\beta_{0,t}^{\text{std}} \equiv \alpha_t$, and $\beta_{k,t} = \beta_{k,t}^{\text{std}} \times \sigma_k$ the change in returns of the tariff-price portfolio associated to one extra article in narrative k on day t .

The ℓ_1 total-variation penalty of the standard fused LASSO promotes *piecewise-constant* paths: coefficients are flat across most trading days, with sparse, sharp transitions on a small number of identified dates. The optimization program in (2) is convex (and globally solvable using the Clarabel interior-point solver in Diamond and Boyd (2016)). Methods which allow for smoother coefficients would allow for too many degrees of freedom for useful estimation in this context, in

³⁹By the end of the sample, as trade deals begin to be signed, the cumulative return returns to near-zero levels.

⁴⁰Bianconi et al. (2021), by creating a long-short portfolio along the trade uncertainty dimension using the Baker et al. (2016) Trade Policy Uncertainty index, finds annual α of about 3-6% in excess of standard Fama-French portfolios over the 1990-2001 trade uncertainty episode.

⁴¹There are two main reasons for the standardization of article counts in $\mathbf{x}$. First, standardization offers numerical stability: raw article counts differ a lot across narratives; standardized sizes keep the design matrix in a range that solvers handle well and reduces the risk of ill-conditioning. Second, standardization guarantees comparable penalties across narratives; otherwise, the penalty’s severity would depend on narrative size, or the penalty would need to be scaled to make it commensurate with each narrative. Out of these options, standardization is preferable because it allows for a single, interpretable penalty λ_{tv} to be maintained. In the visual representations, the transformation is easily reversed to present “true” per-article figures.

addition to losing the the desirable “narrative regime” intuition.

Figure D.5 displays the coefficient paths for each $\beta_{k,t}$ (i.e., the per-article effects) with bootstrap-obtained confidence bands. The per-article narrative regimes exhibit jumps in the piecewise-constant coefficients that correspond to genuine shock events, and the aggregate impact, obtained by multiplying the per-article effect by the article count, is economically salient, especially at these jumps.

Consider, for example, the narrative on the “Constitutional Challenge to Presidential Tariff Authority” in Figure 6. The narrative regime Figure 6(a) has two jumps, coinciding to the major event dates for the narrative. On May 28 and 29, two injunctions were issued against the tariff regime, one of which was stayed on the 29th. On June 3, a stay was granted also against the second, effectively keeping the tariff regime in place pending future appeals.⁴² (Notably, the timing and intensity of both jumps emerge fully from the LASSO estimation: that they occur at real-world event shocks is further validation that the methodology is identifying meaningful variation.)

Moreover, by considering the product of the per-article narrative regime and the number of articles on a day (Figure 6(b)), it becomes possible to quantify the aggregate informational contents of a narrative on some day. For instance, the narrative on constitutional challenges to presidential authority explains a -36 bps decrease in the daily price-impact of tariffs on May 29, and a +27 bps increase on June 3. In the next section, I take use this total narrative signal (i.e., the product of the per-article narrative regime and the article count) to elicit stocks’ exposure to narratives and explain stock returns.

Choice of Total Regularization Penalty and Robustness Checks The implementation of the fused LASSO is dependent on the choice of λ_{TV} . Because the model is contemporaneous and not predictive, traditional selection criteria for λ_{TV} , which depend on out-of-sample validation, are not an appropriate fit. I propose a selection criterion which maximizes the mean episode size produced by the jumps. This criterion and alternatives criteria are discussed in Appendix D.2.

Appendix D.3 presents additional robustness checks for insensitivity to the choice of λ_{TV} , a comparison to other methods, and a detailed explanation of the bootstrap standard error construction. I document that the narrative regime coefficient paths are robust to the choice of λ_{TV} within a broad interval of candidate λ . Furthermore, I confirm that the time-variation is key to the setting: using the fused-LASSO effective degrees of freedom, the approximate F-test rejects the null of time-constant coefficients ($F(57, 11) = 23,312.89, p < 0.001$).

Structural origins of narrative informativeness I call the absolute value of the per-article narrative regime $|\beta_{kt}|$ the narrative’s *informativeness*. Motivated by the finding that narratives are future-oriented and cluster around predictions (see Appendix K.2), I show that narrative informativeness is negatively associated with the coherence of within-narrative predictions. In particular, the more trivially-unanimous the articles within a narrative become in the predictions they make,

⁴²See, e.g., United States Court of Appeals for the Federal Circuit (2025) for the May 29 stay, following the May 28 injunction, and ? for the June 3 stay following the May 29 injunction.

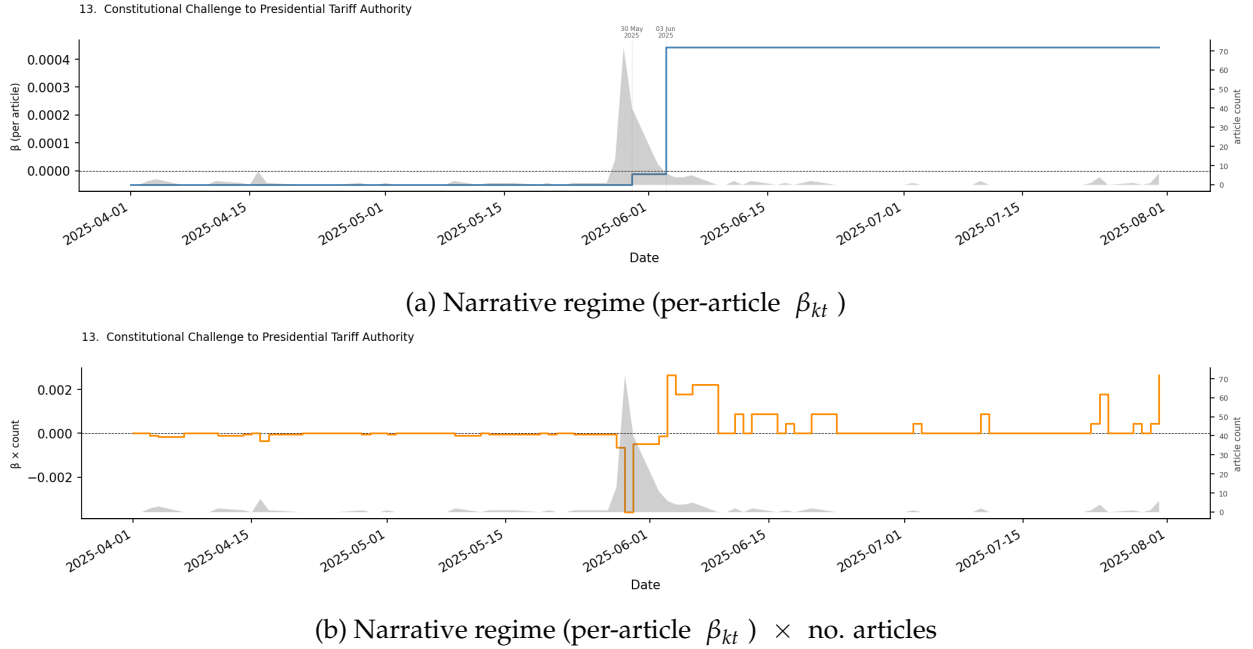


Figure 6: Narrative Regime: “Constitutional Challenge to Presidential Tariff Authority”

Panel A displays daily coefficients β_{kt} from the total variation regularized fused-Lasso specification linking standardized article counts to the contemporaneous tariff price for the narrative bearing on constitutional challenges to presidential authority to impose tariffs. The blue line is the estimate of the narrative regime (the per-article β_{kt}). The vertical axis is the associated change in the commodity tariff long-short portfolio’s simple daily return per additional article. The lower panel multiplies that coefficient by the days raw article count, so its axis is in the same units as the factor return: a reading of 0.001 is 0.1 percent, or 10 basis points. The yellow line in Panel B presents the product of the two series in Panel A: the per-article $\beta_{kt} \times$ the article count. This gives the aggregate effect. The gray shaded area in the background of both panels is the article count (right vertical axis). (Article counts are standardized only inside the estimation; the lines are converted back to raw-article units.)

the more likely this is to be a reflection of the narrative’s contents already being completely priced in. In other words, a necessary condition for an event shock to be informative is that it must not have been fully and perfectly anticipated by the narrative; otherwise, it would already have been fully reflected in prices. Appendix K.4 contains this finding and provides a discussion.

6 Constructing Market-Implied Exposure to Narratives & Measures of Narrative Disagreement

In this section, I use narrative signals (which I define as the per-article narrative regimes multiplied by their article counts) to price stocks of the S&P 500, and use stocks’ exposure to narratives to construct measures of narrative disagreement and narrative cacophony.

6.1 Stock Market Data

I obtain daily equity data for S&P 500 constituents from CRSP. The raw panel covers 485 stocks, restricted to the April 1–July 31, 2025 window (84 trading days) to match the narrative signal dataset.

The primary outcome variable is *log-turnover*, defined as

$$\log \text{TO}_{i,t} := \log \left(\frac{\text{Volume}_{i,t}}{\text{SharesOutstanding}_{i,t}} \right), \quad (3)$$

which scales trading activity by shares outstanding (a proxy for the tradable share base), and removes the mechanical size component from dollar-volume comparisons.

I construct control variables from the same CRSP data: absolute daily return $|r_{i,t}|$ and lagged log-turnover $\log \text{TO}_{i,t-1}$. Industry classification uses the 6-digit NAICS code available in CRSP data, aggregated to 2-digit groups for fixed-effect estimation. From the narrative data, I also retain the log of the total number of tariff-related news articles published on a given day to control for overall newsworthiness of the subject and event shocks.

6.2 Narrative Signal Construction

Definition 6.1. I define the *narrative signal* for narrative k on trading day t as

$$F_{k,t} = \underbrace{\hat{\beta}_{k,t}}_{\text{per-article narrative regime}} \times \underbrace{n_{k,t}}_{\text{article count}}.$$

$F_{k,t}$ is thus exactly the total contribution of narrative k to the market’s belief of aggregate tariff price impact⁴³ on day t , expressed in simple return units, and is computed as the product of the per-article $\hat{\beta}_{k,t}$ and the number of articles in the narrative $n_{k,t}$.

Figure D.6 presents the signals $F_{k,t}$ for all narratives (Figure 6(b) shows the signal for the narrative on constitutional challenges to presidential tariff authority). The product structure embeds a joint filter: a narrative that is heavily covered but uninformative contributes nothing to the signal ($\hat{\beta}_{k,t} \approx 0$); a hypothetically-informative narrative which receives no attention in the press likewise contributes nothing ($n_{k,t} \approx 0$). Only narratives that are simultaneously prominent in the news and informative generate non-zero signals.

6.3 Stocks’ Exposure to Narratives: A Mixed-Effects Decomposition

With 84 trading days and 15 narratives, a stock-by-stock OLS would leave almost no degrees of freedom per stock. Motivated by the idea that firms within the same industry share common exposure to narrative shocks, I use a mixed-effects model that pools stocks within an industry and shrinks noisy stock-level estimates towards their industry means (Henderson, 1975). This is

⁴³The simple return of the long-short portfolio of commodities, sorted by statutory exposure (section 5).

similar to an industry-pooled OLS, but more explicitly accounts for group structure. Estimated coefficients are essentially identical to standard industry-pooled OLS (the largest difference is 2.48×10^{-13} , see Table E.1).⁴⁴

For stock i in industry $g(i)$ on day t , I estimate:

$$r_{i,t} = \alpha_{g(i)} + \sum_{k=1}^K \gamma_{g(i),k} F_{k,t} + \sum_{k=1}^K u_{i,k} F_{k,t} + \varepsilon_{i,t}, \quad (4)$$

where $K = 15$, $\alpha_{g(i)}$ is an industry intercept, $\gamma_{g(i),k}$ is the industry-level loading on narrative k , and $u_{i,k}$ is the stock-specific deviation from the industry mean loading. I assume

$$u_{i,k} \stackrel{\text{iid}}{\sim} \mathcal{N}(0, \sigma_k^2), \quad \varepsilon_{i,t} \stackrel{\text{iid}}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2).$$

I estimate the model separately for each industry. The variance components are estimated by restricted maximum likelihood (REML) and the resulting random effects are measured using BLUPs (Patterson and Thompson, 1971; Henderson, 1975). Thus stocks whose returns carry little information about narrative k are pulled toward the industry mean $\gamma_{k,g}$, avoiding the in-sample overfitting that would plague OLS with only 84 time-series observations.

Likelihood-ratio tests for the random-effects (see Table E.2) components reveal cross-stock heterogeneity in narrative loadings in only two of the 21 industry groups: Utilities ($p < 0.001$), and Machinery and Electronics Manufacturing ($p < 0.01$) – precisely the sectors where there is plausible product-level heterogeneity in tariff exposure and hence surrounding narratives (e.g., semiconductors vs. defense vs. industrial machinery). In “flat” industries such as Finance ($p = 0.999$) and Information/Media ($p = 1.000$), a lack of heterogeneity is natural: in most industries, the same tariff narratives govern most stock-specific discourse, and they apply in the same way across firms. Because the within-industry idiosyncrasy is not statistically significant for all but two industries, I omit these and take the industry loading as the stock loading for greater parsimony – and for consistency with standard industry-pooled OLS. The total stock-level loading is, then,

$$\lambda_{i,k} = \gamma_{k,g(i)}.$$

Figure E.1 reports per-industry R^2 of the asset-pricing exercise with narrative signals. As expected, there is significant heterogeneity by industry, and the qualitative direction is the desired one: industries like healthcare with little exposure to tariffs have low R^2 (around 5%) while those related warehousing and mining, oil and gas, have high R^2 (over 30%).

There are two stocks with singleton industries, which renders the industry-pooling structure meaningless. I drop these from the main analysis, retaining 483 stocks, 84 trading days, and 15 narratives.

⁴⁴The mixed-effects model specification I use is related to the multilevel modeling framework of Gelman and Hill (2006) and to the shrinkage estimators of signal loadings such as ?.

	Tariff L-S	Narratives	Topic models				
R^2 (within)	0.027	0.178	0.015	0.085	0.117	0.121	0.141
R^2 (full, incl. FE)	0.036	0.185	0.024	0.093	0.125	0.129	0.149
Text			Articles	Articles	Articles	Articles	Stories
Weight			Shares	Counts	Counts	Counts	Counts
K		15	5	5	15	15	15
Regimes		✓				✓	✓

Table 1: Summary of R^2 of Daily Stock Returns by Model

Each column is a time-series OLS regression run separately for each stock: its daily return on an intercept and a single regressor: the predicted return for each stock by that model ($\Lambda'F$, the sum of the predictor variables multiplied by their loadings). The models used are the Tariff Long-Short Portfolio/Factor, Narrative signals, or a battery of Topic Models and hybrid approaches (Appendix I). Topic models start from the implementation closest to [Bybee et al. \(2024\)](#) (full article text; prominence captured by shares; 5 topics selected by a LASSO for their ability to explain stock returns; and no regimes, i.e., constant weight) and eventually work up to a hybrid approach most resembling my narrative pipeline except that the input remains topic models and not narratives (stories from step 1 of my methodology as the text inputs; article counts as weights; 15 topics selected purely by topic size; regimes). All text-analysis methods use industry-level exposure; the tariff-commodity portfolio is built from stock-level exposure. The sample is 483 S&P 500 constituents with returns on all 84 trading days from 1 April to 31 July 2025. Returns are raw CRSP daily returns.

Comparing narratives, the tariff factor, and topic modeling Table 1 presents a comparison of narrative signals to the tariff long-short portfolio factor and to topic modeling approaches. The tariff factor alone, without being decomposed by narratives, explains only 2.7% of returns – while the narrative signals explain around 17.8%. I consider several topic modeling approaches, taking as baseline the one from [Bybee et al. \(2024\)](#) and successively adapting it to my narrative pipeline. The full narrative pipeline is has 52% more explanatory power than the median topic modeling alternative, and 26% more explanatory power than the best topic modeling alternative. The latter differs from my pipeline only in that it uses narrative scoring and clustering instead of topic modeling; in fact, it even starts from my step 1 (story extraction) and so is run on the basis of exactly the same summarized articles as my narrative methodology. Topic modeling approaches are discussed in detail in Appendix I.

Out of sample validation The time series is too small for meaningful time-split and conventional out-of-sample (OOS) validation. Instead, as a validation of the narrative signals and industry pooling approach, I perform a cross-sectional OOS check: within each NAICS-2 industry I randomly exclude half of the stocks, estimate γ_g , and assign that γ to the held-out stocks on the same dates. Across 100 splits, held out returns line up with $\hat{\gamma}^{\text{train}} \cdot F_t$ with coefficient approximately 1 (with and without stock FEs $\hat{\beta}_\gamma = 0.93 - 0.94$; never reject $\hat{\beta}_\gamma = 1$) and the R^2 is stable (Mean OOS within- $R^2 = 0.16 - 0.17$; full-sample $R^2 = 0.18$). Results are reported in Table E.2. Topic

models, meanwhile, attain a lower R^2 in these validation checks: the narratives have 27% higher R^2 than the next-best topic modeling alternative, and 55% higher R^2 than the median approach.

6.4 Narrative Disagreement & Cacophony: Construction and Properties

Using this estimation, I construct measures of asset-level⁴⁵ price-derived narrative disagreement and narrative cacophony. Two desiderata motivate the design: first price-derived measures have the advantage of being directly based on the implications of each narrative for each stock; second, measures of disagreement should capture the geometry of stocks' returns' exposure to narratives (rather than reduce to a unidimensional statistic). I, therefore, begin with a measure of narrative-induced price pressure:

Definition 6.2. The *realized narrative-induced price pressure* of narrative k to stock i 's tariff-driven price movement on day t :

$$c_{i,k,t} = \lambda_{g(i),k} \times F_{k,t}. \quad (5)$$

which varies at the industry $\times$ day $\times$ narrative level and combines the stock's (industry-level) exposure to the narrative $\lambda_{g(i),k}$ with the time-varying narrative-implied change in the intensity of tariffs' price impacts $F_{k,t}$.

Figure 7 presents realized narrative exposure ($c_{i,k,t}$) averaged across stocks over time – where the average is computed separately for non-negative and non-positive contributions to show the heterogeneity. This graph allows for an immediate answer to the frequently-asked question: “what’s the story in the market today?” It is possible to immediately see the price movements associated to particular narratives, that is, to identify why and by how much a returns moved in a given direction of a particular day.⁴⁶ For example, on July 31, 2025 – the day after a US-Japan deal set a 15+% tariff on Japanese auto-sector imports – the narrative on the automotive sector’s adaptation strategies explained 55% of Ford’s return that day (an auto-narrative-attributable 0.94p.p. increase, relative to a 1.7% return), while explaining -7% of the financial firm Fiserv’s return.

Using this measure of realized narrative price-pressure, I then construct the following measures of narrative preponderance and concentration.

Definition 6.3. The *total realized narrative-implied tariff exposure* of narrative-driven price pressure (Figure E.4a) is given by:

$$\tau_{i,t} = \sum_{k=1}^K |c_{i,k,t}|, \quad (6)$$

Definition 6.4. *Narrative dispersion* (Figure E.4b) is defined via the Shannon entropy of the nor-

⁴⁵Because of the precise estimation, in this paper these vary on the industry level; but with an alternative estimation, one could use the construction proposed below to derive stock-level disagreement.

⁴⁶While this graph presents the market-average narrative-implied price movements, the graph can be reconstructed for any given stock or industry. See Appendix E.3 for industry-level graphs.

malized exposure shares. For $\rho_{i,k,t} = \frac{|c_{i,k,t}|}{\sum_{k'} |c_{i,k',t}|} \in [0, 1]$.⁴⁷

$$H_{i,t} = - \sum_{k=1}^K \rho_{i,k,t} \log \rho_{i,k,t}, \quad (7)$$

which has codomain $[0, \log K]$. $H_{i,t} = 0$ if all of a stock's realized tariff exposure on day t are concentrated in a single narrative; as there are 15 narratives, $H_{i,t} = \log 15 \approx 2.71$ if narrative loadings are dispersed and all 15 narratives contribute equally. The median stock-day has $H_{i,t} = 1.98$, or about 73% of the maximal value. This corresponds to $e^{1.98} \approx 7.24$ effective equal narratives on the median stock.

Definition 6.5. *Directional disagreement* (Figure E.4c) is a measure of sign conflict:

$$D_{i,t} = 1 - \frac{|\sum_k c_{i,k,t}|}{\sum_k |c_{i,k,t}|} \in [0, 1]. \quad (8)$$

That is, polarization captures the share of narratives which contradict each other (i.e., cancel out) irrespective of the level of pressure they exert or their number. $D_{i,t} = 0$ if all active narratives predict the same direction for stock i (full alignment); $D_{i,t} = 1$ if positive and negative narratives perfectly cancel. The median $D_{i,t}$ is 0.75, meaning that on a typical stock-day, 75% of the gross narrative exposure cancels between opposing-direction narratives – reflecting the genuine directional tension in the 2025 tariff narrative space.

Conceptual differences between measures of disagreement Total narrative-implied exposure τ_t is conceptually distinct from narrative dispersion H_t : the asset may have high τ_t with low H_t (one dominant narrative) or high τ_t with high H_t (several narratives contributing equally). Including both in the analysis allows me to control for simple channels like “more narrative activity always equals more volume,” and to check whether volume is driven by narrative concentration or by aggregate narrative pressure.

Directional disagreement D_t , in turn, captures a dimension conceptually distinct from dispersion H_t : a stock can have high or low entropy (many or few influential narratives) with either high or low directional conflict. For instance, two non-trivial-exposure narratives equal in magnitude but having opposite signs leads to a low-dispersion, high-directional-disagreement environment; meanwhile, a setting with many narratives all with the same sign has high dispersion but low polarization. In fact, the inclusion of H and D in the same analysis allows for dispersion to be interpreted as a measure of the multitude of salient conceptual paradigms, or the fragmentation of the informational environment, and for directional disagreement to be taken as a measure of how much disagreement on the implications of information there is.

Appendix G confirms that τ, H, D , and $H \times D$ are empirically distinct.⁴⁸

⁴⁷This and the following definition are, of course, valid only if $\tau_{i,t} = \sum_k |c_{i,k,t}| \neq 0$. This is never a binding constraint in the data.

⁴⁸In short, within-stock correlations are $\rho(H, D) = 0.24, \rho(H, \tau) = 0.23$, and $\rho(\tau, D) = 0.26$; within-day correlations are $\rho(H, D) = 0.21, \rho(H, \tau) = 0.23$, and $\rho(\tau, D) = 0.01$; and two-way are $\rho(H, D) = 0.25, \rho(H, \tau) = 0.16$,

Definition 6.6. *Narrative cacophony* (Figure E.4d) is characterized by the presence of many narratives with contradictory pricing implications:

$$\text{narrative cacophony}_{i,t} = H_{i,t} \times D_{i,t}. \quad (9)$$

Narrative cacophony can be taken as a natural aggregate-level analogue to ambiguity: a set of priors is truly ambiguous if an agent simultaneously holds many beliefs *and* if these beliefs have different implications for behaviour. The mere multiplicity of beliefs alone – if they are all behaviourally equivalent – is not itself a sign of ambiguity, just as the presence of many narratives per se need not be indicative of genuine cacophony. It is reasonable to expect agents to be averse to narrative cacophony: as cacophony increases, so does the complexity of interpretation of the underlying news.

7 Volume and Price Analysis

In this section, I test the conjecture that narrative cacophony leads people to trade less on their information, and that this prevents the market from aggregating information. First, I test the hypothesis that narrative cacophony decreases volume. Second, I check that when volume is low due to cacophony, the market aggregates information less well. Third, I verify that information is incorporated with a delay.

To do so, I exploit the structure of $\tau_{i,t}, H_{i,t}, D_{i,t}$ and $H_{i,t} \times D_{i,t}$. Conditional on the estimated loadings $\{\lambda_{g(i),k}\}$, the day-to-day variation of $\tau_{i,t}, H_{i,t}, D_{i,t}$ and $H_{i,t} \times D_{i,t}$ comes entirely from changes in the narrative signal values $\{F_{k,t}\}$, which are determined by the importance of tariff-related narratives to explaining variation in tariff-attributable commodity price changes, and not by the trading activity of any individual stock.

7.1 Hypothesis 1: Narrative Cacophony and Volume

The first hypothesis bears on the relationship between narrative cacophony and volume, and checks whether there is a dampening effect on volume. To test this hypothesis, I run the following regression

$$\log \mathcal{V}_{i,t} = \alpha_i + \gamma_H H_{i,t} + \gamma_D D_{i,t} + \gamma_{H \times D} H_{i,t} \times D_{i,t} + \gamma_\tau \tau_{i,t} + \mathbf{x}'_{i,t} \boldsymbol{\psi} + \varepsilon_{i,t} \quad (10)$$

identifies $\gamma_{H \times D} \equiv \gamma_{\text{cacophony}}$ from within-stock, over-time variation in dispersion and directional disagreement. The stock fixed effect α_i absorbs all time-invariant characteristics (baseline turnover level, size, sector, investor base composition, etc.). The controls $\mathbf{x}_{i,t}$ include absolute returns $|r_{i,t}|$, lagged volume $\log \mathcal{V}_{i,t-1}$, the overall newsworthiness of tariffs that day ($\log$ article

and $\rho(\tau, D) = 0.12$. Moreover, within quartiles of D , $\rho(H \times D, D)$ decreases, from 0.93 in the lowest-directional-disagreement quartile to 0.25 in the highest. The pattern is the same for quartiles of H , falling from 0.64 to 0.26 from the lowest- to highest-dispersion quartiles. This confirms that cacophony is not merely a mechanical transformation of either H or D separately.

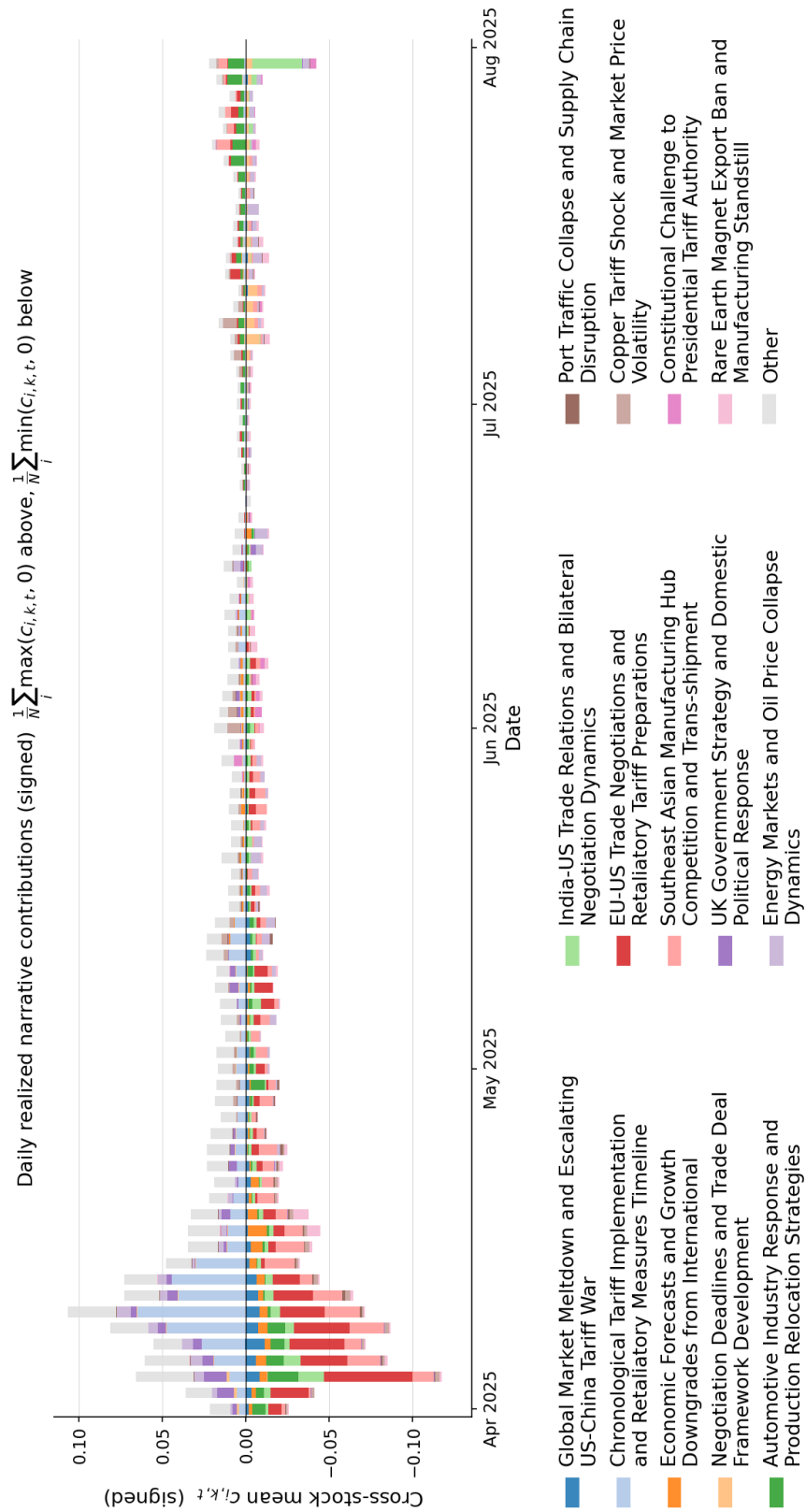


Figure 7: Daily narrative contributions to stock returns

This graph presents the signed (i.e., non-negative and non-positive, separately) contributions of c (narrative-signal-implied return shifts) for S&P500 stocks, averaged to produce the daily market-wide figure.

count), and the contemporaneous economic impact of tariffs (as measured by the return of the commodity long-short portfolio). Standard errors are clustered two-way (stock and day), with robustness checks at alternative clustering levels (including two-way industry-day, bootstrapping, and others, all in Table F.1). The cacophony hypothesis posits that $\gamma_{H \times D} < 0$.

Table 2 reports the main result for tests of Equation 10. Except the baseline with no controls (which recovers the desired negative sign but fails to garner statistical significance), the cacophony interaction term is always robustly negative and statistically significant.⁴⁹ Including controls for absolute returns, lagged turnover, (logged) news article count and the commodity long-short portfolio (from which narrative signals are constructed) means that the narrative cacophony effect cannot be explained by the underlying commodity portfolio from which narrative signals are constructed or the usual mechanical measures of volume.

As cacophony is defined via an interaction term, its magnitude is difficult to interpret in isolation. A one-standard-deviation increase in both dispersion and directional disagreement lowers turnover by about 5% (1.6 s.d.). It is also possible to interpret the impact of narrative cacophony by considering the share of days on which – as a result of the interaction term – narrative dispersion and directional disagreement have positive or negative impacts on volume. With the inclusion of controls, the linear terms for both are positive. However, due to the cacophony term, dispersion has a positive marginal effect on turnover on only 17% of days, and directional disagreement has a positive marginal effect on turnover on only 21.1% of days (see Column 6 of Table 2). At the median level of directional disagreement D , a 1 s.d. increase in dispersion H lowers turnover by about 2.4%. At the median level of dispersion H , a 1 s.d. increase in directional disagreement D lowers turnover by about 1.6%.

Robustness Table F.1 verifies that the statistical significance of results is not special to a particular choice of clustering by replicating the analysis with two-way clusters by industry and day, with and without wild bootstrapping; industry clusters with bootstrapping; stock-only clustering; Driscoll-Kraay 3-day and 5-day lag clustering; and moving-block bootstraps with 5-day blocks. Table F.2 confirms that the result is robust to replacing contemporaneous absolute returns by lagged absolute returns. Table F.8 confirms that the interaction term is not a mechanical feature of the functional form of H by using an alternative measure of narrative dispersion (the Herfindahl-Hirschman Index; cf, e.g., Hirschman (1964)).

In Tables F.5 and F.7 I check that the negative cacophony effect is robust to the inclusion of controls for standard measures of uncertainty: VIX, the bid-ask spread, and the Tariff Policy Uncertainty (TPU) index,⁵⁰ the tariff-specific variant of the Economic Policy Uncertainty index (see Baker et al., 2016, for the original EPU) – as well as the topic-modeling derived analogous measure of topic cacophony. (Tables F.4 and F.6 contain the corresponding horse-race models.) In Table F.3,

⁴⁹The slight moderation of the effect (with respect to Column 2) with the inclusion of controls is expected and indeed desirable if one believes that narratives are supposed to reflect market fundamentals rather than something completely orthogonal to classic variables used in the study of financial markets.

⁵⁰Obtained from https://www.policyuncertainty.com/trade_uncertainty.html

I verify that the cacophony volume-dampening effect is not merely driven by the difference between stocks with high and low exposure to tariffs: it persists (and is even 16-18% stronger) on the subsample of stocks with high exposure to tariffs as measured either by narrative-implied exposure (high τ) and high statutory exposure. Directly controlling for high statutory tariff exposure itself likewise does not change the result.

7.2 Hypothesis 2: Narrative Cacophony and Explainability of Returns

In the second hypothesis, I ask are the stock-days on which narrative cacophony is most potent (i.e., days on which a considerable share of volume is suppressed due to cacophony) also the days on which returns are harder to explain? I begin by sorting stock-days by the share of explainable volume foregone due to cacophony. Let

$$\frac{|\hat{V}_{\text{cacophony}}|}{\hat{V}_{\Gamma'X}} \quad (11)$$

where $\hat{V}_{\text{cacophony},it} = \gamma_{H \times D} H_{it} \times D_{it}$ is the predicted level of volume stifled by cacophony, as estimated by Column (6) of Table 2, $\Gamma'X$ is the predicted total level of volume for stock i on date t using set of controls from the same regression excluding stock fixed effects. (For robustness, I consider also $\frac{|\hat{V}_{\text{cacophony}}|}{\hat{V}_{\Gamma'X + \text{stock FE}}}$ where $\Gamma'X + \text{stock FE}$ uses the full set of controls including the stock fixed effects.)

Figure 8 presents the results of a regression of returns on narrative signals, by quartile of the slope-only relative shares of cacophony-suppressed volume as in Equation 11, with the fixed-effect variant presented in Appendix I. The regression for each quartile is run separately. Narrative-signal within-stock R^2 falls from about 25.6% in the lowest quartile to less than 0.5% in the highest. CAPM adjusted R^2 falls from about 55.1% to about 28.6%. Figures F.3 and F.4 confirm that the pattern is robust to the inclusion of controls for realized volume, the tariff long-short commodity portfolio, and a host of other controls, and to different configurations of fixed effects. Taken together, these results suggest that when narrative cacophony stifles a significant share of trading volume, markets are less well-explained by public information, as measured by narrative beliefs themselves, or even by conventional asset-pricing models.

The measures of $\hat{V}$ on the denominator isolate explainable volume, or, more precisely, volume which can be explained by tariff-related variables, more mechanical relationships (such as persistence in volume) or stock-specific features. Random shocks or trading for informational non-tariff-related reasons (e.g., other geopolitical tensions) are left in the residual and hence excluded.

The quotient, in turn, identifies the relative importance of the foregone volume associated to cacophony as a share of the overall explainable volume. The level of foregone volume alone can be misleading: if a particular stock-day has a low level of cacophony – and hence a low level of cacophony-attributable volume – it would be all too easy to dismiss cacophony as an important factor for that stock-day. Yet, if there is little else happening for that stock on that day, it could be

	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion $H_{i,t}$	-0.082 (0.126)	0.727*** (0.179)	0.421*** (0.120)	0.411*** (0.116)	0.399*** (0.153)	0.379*** (0.139)
Directional Disagreement $D_{i,t}$	0.058 (0.375)	1.843*** (0.455)	1.101*** (0.329)	1.072*** (0.327)	1.055*** (0.393)	1.107*** (0.379)
Cacophony $H_{i,t} \times D_{i,t}$	-0.020 (0.207)	-1.019*** (0.233)	-0.604*** (0.167)	-0.599*** (0.164)	-0.590*** (0.196)	-0.608*** (0.187)
Narrative Price Pressure $\tau_{i,t}$				0.473 (0.390)	0.354 (0.814)	0.337 (0.743)
$\ln(1 + \text{no. articles}_t)$					0.009 (0.070)	0.009 (0.065)
Commodity long-short return						-10.048** (4.911)
$ r_{i,t} $		7.729*** (0.959)	8.306*** (0.746)	7.903*** (0.804)	7.913*** (0.803)	7.828*** (0.725)
$\ln \text{TO}_{i,t-1}$		0.761*** (0.017)	0.456*** (0.031)	0.446*** (0.028)	0.446*** (0.027)	0.449*** (0.028)
Stock FE			✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572
Within R^2	0.001	0.718	0.425	0.427	0.427	0.436
Overall R^2	0.001	0.718	0.775	0.776	0.776	0.779
$\partial \log \text{TO} / \partial H$ evaluated at:						
$D = 0.553$ (p10)	-0.093	0.163	0.087	0.080	0.073	0.043
$D = 0.698$ (p25)	-0.096	0.015	-0.001	-0.007	-0.012	-0.045
$D = 0.827$ (p50)	-0.098	-0.116	-0.079	-0.084	-0.089	-0.124
$D = 0.926$ (p75)	-0.100	-0.217	-0.139	-0.144	-0.147	-0.184
$D = 0.968$ (p90)	-0.101	-0.260	-0.164	-0.169	-0.172	-0.209
Sample share $\partial \log \text{TO} / \partial H > 0$	0.0%	27.0%	24.9%	24.1%	23.4%	17.0%
$\partial \log \text{TO} / \partial D$ evaluated at:						
$H = 1.71$ (p10)	0.025	0.100	0.068	0.047	0.046	0.067
$H = 1.846$ (p25)	0.022	-0.039	-0.015	-0.034	-0.034	-0.016
$H = 1.977$ (p50)	0.019	-0.172	-0.094	-0.112	-0.112	-0.096
$H = 2.092$ (p75)	0.017	-0.289	-0.163	-0.181	-0.179	-0.166
$H = 2.172$ (p90)	0.016	-0.371	-0.212	-0.229	-0.227	-0.215
Sample share $\partial \log \text{TO} / \partial D > 0$	100.0%	19.6%	21.3%	18.0%	18.0%	21.1%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Standard errors, in parentheses, are two-way clustered by stock and by day.

Table 2: Narrative Cacophony and Volume

The dependent variable everywhere is log turnover. Dispersion $H_{i,t}$ is measured by the entropy of stock i 's distribution of narrative price shocks on day t ; directional disagreement $D_{i,t}$ measures the sign conflict of those narratives' price implications by the share of narrative price implications which survive a "netting out"; and cacophony is their product. Column (1) includes only these three terms. Column (2) adds the standard volume controls: absolute return and lagged log turnover. Columns (3)–(6) add stock fixed effects and the rest of the controls: Column (4) adds narrative-implied tariff exposure $\tau_{i,t}$, column (5) the log number of articles, and column (6) the return on the commodity long-short tariff portfolio. The lower panels evaluate $\partial \log \mathcal{V} / \partial H$ at percentiles of D and $\partial \log \mathcal{V} / \partial D$ at percentiles of H , and report the share of stock-days on which each marginal effect is positive.

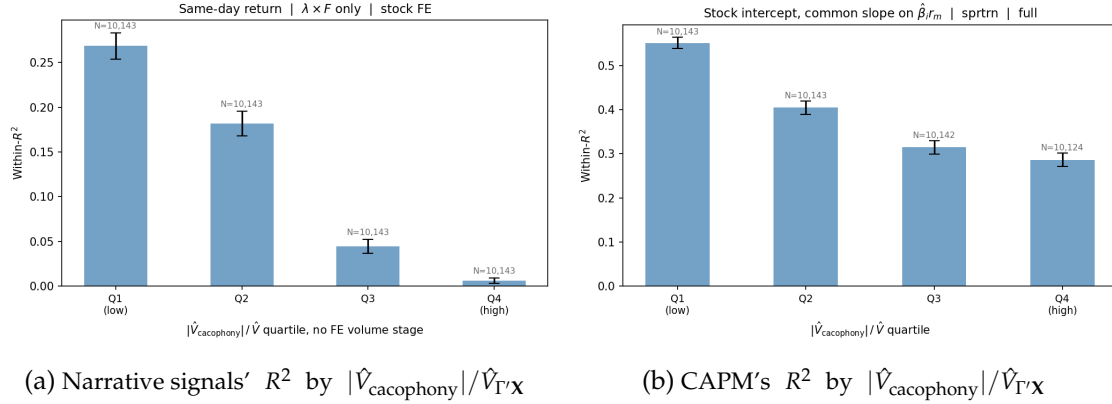


Figure 8: S&P 500 Stocks Return R^2 by Quartile of Cacophony-Stifled Volume Share

Stock-day observations are sorted by $|\hat{V}_{\text{cacophony}}|/\hat{V}$, where $\hat{V}_{\text{cacophony}} = \hat{\gamma}_{H \times D}(H \times D)$ is the contribution of the entropy $\times$ sign-conflict term to fitted log turnover. The denominator is the slope component $\hat{V}_{\Gamma'X}$; the fitted volume with the stock FE, $\hat{V}_{\Gamma'X+\text{stock FE}}$, follows the same pattern and is reported Figure F.1. The left panel reports the within- R^2 from a regression of the same-day return on the narrative-signal prediction $\lambda'_t F_t$, with stock fixed effects and stock-by-stock slope. The right panel reports the adjusted R^2 from a CAPM estimation (with stock FEs). Error bars indicate 95% intervals, and N is the number of stock-days in the quartile. The narrative-signal within- R^2 falls from about 25.6% in the lowest quartile to less than 0.5% in the highest; CAPM adjusted R^2 falls from about 55.1% to about 28.6%.

that the cacophony is still a dominant force. (Analogously, a day in which the amount of volume foregone due to cacophony is large might still not be a day on which the cacophony effect is particularly strong if the overall trade volume is sufficiently high.)

Robustness Appendix H checks that results are not a mechanical function of high-vs-low volume days, and that the sort on cacophony matters. (Holding volume fixed, a higher cacophony-suppressed share still means lower R^2 .) Moreover, I verify that the pattern persists even controlling for the overall narrative-implied predicted return magnitude $|\Lambda'F|$. In Figure F.1, I present the results for $\hat{V}_{\Gamma'X+\text{stock FE}}$, which follow the same patterns. In Table F.2, I include both the CAPM market factor and narrative signals as a control, and compute the relative contribution of both models to the adjusted R^2 (via the Shapley (1953) values of each model, following Lipovetsky and Conklin (2001) and Shorrocks (2013)). The relative contribution of narrative signals to overall R^2 follows a similar decreasing pattern, suggesting that narratives become increasingly less influential (from explaining about 25% of adjusted R^2 to about 13%) as cacophony stifles volume: the explanatory power of narrative signals wanes in both absolute and relative terms.

7.3 Hypothesis 3: Narrative Cacophony and Delayed Information Aggregation

The results from Hypothesis 2 – about R^2 of stock returns decreasing with the share of volume suppressed by cacophony – are consistent with two interpretations: either markets are becoming less informationally efficient in cacophonous environments (i.e., the R^2 is inefficiently low), or there is just (relatively) less public information and markets are noisier or more driven by private

information (i.e., the low R^2 is at the “correct” level).

In contemporaneous and forecasting regressions, I test whether higher cacophony share slows the incorporation of the narrative prediction $\Lambda'F_{it} = \sum_k \lambda_{ik} F_{kt}$. When cacophony suppresses more trading, markets becomes less informationally efficient (à la Fama, 1970): less of the same-day return should line up with $\Lambda'F_{it}$, and more of the prediction should remain in the next-day return. I estimate the following regressions by quartiles of share of explainable volume suppressed by narrative cacophony $|\hat{V}_{\text{cacophony}}|/\hat{V}$ (for measures of $\hat{V}$ cf Equation 11):

$$\begin{aligned} r_{i,t+1} &= \gamma_{\Lambda F}^{\text{next-day}}(\Lambda'F)_{it} + \delta'(r_{it}, X_{it}) + FE_{it} + \varepsilon_{i,t+1}. \\ r_{it} &= \gamma_{\Lambda F}^{\text{same-day}}(\Lambda'F)_{it} + \delta'(X_{it}) + FE_{it} + \varepsilon_{i,t+1}. \end{aligned} \quad (12)$$

where the control variables are bid-ask spread, narrative dispersion H , directional disagreement D , and cacophony $H \times D$. Delayed incorporation of information (a kind of “momentum” effect) means $\gamma_{\Lambda F}^{\text{next-day}} > 0$. Hypothesis 3 posits that markets become less informationally efficient with cacophony-stifled trade. That is, $\gamma_{\Lambda F}^{\text{next-day}} > 0$ should increase with quartile and $\gamma_{\Lambda F}^{\text{same-day}}$ should decrease with quartile. More concretely, defining the quartile-specific versions of $\gamma_{\Lambda F}^t$ (by the same cacophony-suppressed volume share splits as in Hypothesis 2), Hypothesis 3 expects:

$$\gamma_{\Lambda F, Q4}^{\text{same-day}} - \gamma_{\Lambda F, Q1}^{\text{same-day}} < 0, \text{ and } \gamma_{\Lambda F, Q4}^{\text{next-day}} - \gamma_{\Lambda F, Q1}^{\text{next-day}} > 0.$$

I run each of the regressions in Equation 12 twice: once as base-lines (without additional controls), and again with the specified controls. For next-day returns, I include a control for the previous day’s realized return to help rule out non-narrative-related autocorrelation or persistence effects. Standard errors are clustered by stock and by day, and Appendix F presents robustness checks with bootstrapping and alternative clustering.

As hypothesized, Table 3 shows that an increase in cacophony-stifled volume corresponds to a decrease in contemporaneous pricing in of narratives, as well as an increase in the delayed incorporation of the previous day’s narrative signals. The magnitudes are pronounced for both: passing from the lowest to highest quartile of share of volume foregone due to cacophony decreases contemporaneous pricing in of information by about 54% (from a coefficient of 1.18 to 0.54, $p = 0.002$), even after accounting for stock and day fixed effects and controls such as narrative disagreement and the bid-ask spread. Passing from the lowest to highest quartile and considering delayed incorporation of information, from the previous day’s narrative signals, paints the opposite picture: in the lowest-cacophony quartile, the past day’s narrative signals had no statistical association with the next day’s returns (0.06), while in the highest-cacophony quartile more than half (0.56; the Q4-Q1 difference being significant at $p = 0.030$) of their signal was being incorporated into the next day’s return (likewise, after controlling for two-way fixed effects, narrative disagreement, the bid-ask spread, and even the previous day’s return). The pattern replicates also in Table F.9, where I include stock FEs in the denominator of predicted volume.

These findings suggest that narrative cacophony stifling trade volume corresponds to a slowing down of the incorporation of information: when the share of cacophony-stifled volume is high,

less of the contemporaneous narrative signal is incorporated and more of the previous day's narrative signal becomes priced in. (Moreover, in both cases, the R^2 of returns by lagged narrative signals increases monotonically; see Figure F.5.)

Robustness. In Appendix H, I confirm that the pattern is attributable to cacophony-stifled volume, and not merely an artifact of realized trade volume. (Volume alone cannot reproduce the slope gradients of the cacophony analysis, and cacophony-suppressed volume retains its significance in pooled regressions with both variables included.) I also confirm that results of this test replicate with alternative clustering (bootstrapping) in Tables F.11 and F.12. In Table F.10, I show that the delayed pricing in effect mostly dissipates by the second day: beyond the first day, effects are qualitatively present but too weak statistically to be definitive.

7.4 Further Discussion

Alternative Text-Based Measures: Topic Modeling & Trade Volume In Appendix I, I repeat the analysis with topic-modeling measures and hybrids between a pure topic-modeling pipeline and the full narrative pipeline (e.g., with the construction of narrative regimes from topics). The cacophony-and-volume result of the pure narrative approach is robust to the inclusion of the analogues to τ , H , D , and $H \times D$ derived from these alternative specifications as additional controls. Moreover, in a horse-race, it outperforms these alternative-text-based-measure-derived measures: 14 out of 18 fail to recover a statistically-significant negative cacophony ($H \times D$ interaction) term; two of the four that do are not robust; and the remaining two still have a magnitude of at most a quarter of the main narrative cacophony result. To the degree that topic models can be thought of as measuring the substance of discourse and narratives the structure the discourse takes, this suggests that the cacophony volume-dampening effect and the interpretational complexity it evokes reside primarily in the structure. That is, agents' reluctance to trade is attributable to *how* news are discussed, and not *what* precisely is being discussed. A multitude of topics is not reflective of the presence of truly different interpretations in the same way that narratives are.

These results reflect the difference between the approaches, not an inherent limitation of either. The conjectured cacophony effect has to do with interpretational complexity, so identifying narratives as distinct interpretational structures is crucial. Topic modeling identifies the substance of each narrative, and hence lose some of the dimensions critical to this application, but obviously important to many others.

External Validity The present data comes from a particularly high cacophony, high uncertainty episode. The degree to which the cacophony mechanism is dominant – i.e., the share of days on which the marginal effect of dispersion or directional disagreement turns negative, and the steepness of the R^2 decline and delayed pricing-in intensity – depends on the precise context: the effect should be similar in magnitude to similarly fragmented, complicated informational environments, and to be weaker but still present in less complicated settings.

	Q1	Q2	Q3	Q4	Q4–Q1 <i>p</i> -value
<i>No fixed effects</i>					
Same day, r_{it}	1.30***	0.61***	0.30**	0.14	0.0002***
Same day, r_{it} (controls)	1.29***	0.58***	0.33**	0.17	0.0003***
Next day, $r_{i,t+1}$	0.18	0.45*	0.39	0.62*	0.180
Next day, $r_{i,t+1}$ (controls)	0.39	0.63***	0.56**	0.67*	0.259
<i>Stock fixed effects</i>					
Same day, r_{it}	1.40***	0.64***	0.33**	0.14	0.0001***
Same day, r_{it} (controls)	1.39***	0.58***	0.34**	0.17	0.0001***
Next day, $r_{i,t+1}$	0.20	0.48**	0.39	0.62*	0.200
Next day, $r_{i,t+1}$ (controls)	0.46	0.67***	0.58**	0.66*	0.325
<i>Day fixed effects</i>					
Same day, r_{it}	0.91***	0.47***	0.31***	0.41***	0.002***
Same day, r_{it} (controls)	0.90***	0.49***	0.32***	0.43***	0.004***
Next day, $r_{i,t+1}$	−0.00	0.20	0.29***	0.42***	0.036**
Next day, $r_{i,t+1}$ (controls)	0.02	0.22	0.33***	0.46***	0.020**
<i>Stock and day fixed effects</i>					
Same day, r_{it}	1.20***	0.61***	0.47***	0.55***	0.0008***
Same day, r_{it} (controls)	1.18***	0.62***	0.47***	0.54***	0.002***
Next day, $r_{i,t+1}$	0.02	0.26	0.34**	0.53***	0.038**
Next day, $r_{i,t+1}$ (controls)	0.06	0.29	0.37***	0.56***	0.030**

Table 3: Same-day and next-day slopes on narrative-predicted return, by quartile of $|\hat{V}_{\text{cacophony}}|/\hat{V}$.

Table entries present the slope on $\Lambda'_i \mathbf{F}_{i,t} = \sum_k \lambda_{g(i),k} F_{k,t}$. Same-day rows use r_{it} as the dependent variable, checking same-day pass-through from narrative-implied return to realized return. Next-day rows use $r_{i,t+1}$, the next day's return of the same stock, checking for a momentum effect. Quartiles are equal-count bins of $|\hat{V}_{\text{cacophony}}|/\hat{V}_{\Gamma\mathbf{X}}$, where $|\hat{V}_{\text{cacophony}}| = |\hat{\gamma}_{H \times D}(H \times D)|$ estimates the amount of foregone trade volume attributable to cacophony, and $\Gamma\mathbf{X}$ is the model-predicted (explainable) volume, excluding stock FEs. Q1 is the lowest ratio and Q4 the highest. The four slope columns are separate regressions, with no fixed effects, stock fixed effects, day fixed effects, or both. The Q4–Q1 test stacks Q1 and Q4. Its fixed effects are quartile-specific, so the Q1 and Q4 slopes equal the slopes in those columns. The stacked regression is clustered on the original stock and the original day, so that any overlap enters the covariance. The Q4 – Q1 *p*-value is a one-sided normal *p*-value, consistent with the the tested hypotheses: $\gamma_{\Lambda F, Q4}^{\text{next-day}} - \gamma_{\Lambda F, Q1}^{\text{next-day}} > 0$, and $\gamma_{\Lambda F, Q4}^{\text{same-day}} - \gamma_{\Lambda F, Q1}^{\text{same-day}} < 0$. Stars on that column use this one-sided *p*-value. Stars on the slope entries are two-sided tests that the slope equals zero: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All standard errors are clustered by stock and by calendar day. For the Q4–Q1 *p*-values in the rows without controls, the covariance is the Cameron–Gelbach–Miller sum of the stock, day, and stock-day pieces. Each piece is multiplied by $[G/(G-1)] \times [(n-1)/(n-k)]$ for G the number of clusters and k the number of regressors, excluding absorbed fixed effects.

Length of the time-series. The short time-horizon window of the analysis here is informed by dates of the “Liberation Day” episode. While the narrative-extraction methodology could be modified to run on decades of data to extract broad paradigms which characterized years of market behaviour, these would lose the granularity and specificity that this application enjoys. In that case, one would expect to recover much higher-level narratives which recur over time: perhaps one about tariffs and trade in general, another about financial crises, and another on geopolitical uncertainty (somewhat in the spirit of [Bybee et al. \(2024\)](#)). However, these would be insufficiently granular to analyze interpretational complexity and narrative cacophony, which is the goal of this paper. Thus, insofar as the goal of the paper is not out-of-sample asset pricing, the shorter time-horizon does not constitute a threat to identification and instead offers a more nuanced perspective on the episode at hand.

8 Conclusion

In this paper, I study the importance of narratives (patterns in the organization and interpret information), and their implications in financial markets. In particular, I propose that when information is difficult to interpret (as measured by narrative cacophony: the presence of many narratives with contradictory pricing implications), agents trade less, and so this information is not incorporated into prices. I develop a novel narrative-extraction methodology and apply it to the Liberation Day episode. I find that narratives have meaningful internal structure: there is a robust internal, within-narrative structure (narratives cluster around predictions, which themselves are organized around proposed mechanisms) which relates to narratives’ economic impacts (narrative market informativeness decreases as learning wanes and within-narrative unanimity obtains). Measures of disagreement across narratives to which a stock is exposed on a given day provide evidence of a narrative cacophony effect: on days on which they are exposed to many narratives with conflicting pricing implications, stocks experience lower turnover – an effect difficult to rationalize under traditional models of disagreement, but which I explain in a theoretical framework. When the share of volume foregone due to cacophony is high, the explanatory power of narrative signals and the CAPM decreases drastically (drops by about 30pp from the lowest to highest quartiles), and markets are slower to incorporate pricing implications from past narrative signals. This paper thus offers a step towards integrating narratives into empirical and theoretical analysis of financial markets, and suggests that the interpretability of information – as measured by these narratives – is an important mediating variable in markets’ ability to incorporate information into prices.

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Appendix: Narrative Cacophony in Financial Markets

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October 31, 2026

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A Similarity function horse-race

To select an appropriate similarity function, I run a horse-race comparison of seven automated scoring methods against human-provided scores from an established benchmark dataset. The evaluation strategy is designed to match the logic of the narrative framework as closely as possible, with particular attention to the extra importance of accuracy in the tails of the similarity score distribution.

A.1 Data

I use the Semantic Textual Similarity Benchmark (STS-B) from the GLUE suite (?). The STS-B contains human-provided similarity scores ranging from 0 (which lumps together both actively dissimilar sentence-pairs and orthogonal ones) to 5 (semantically equivalent) for sentence pairs drawn from a variety of natural text sources, including news headlines, image captions, and user forums, and spanning a variety of contextual domains. The scores are averages across multiple independent annotators, which reduces idiosyncratic measurement error and makes STS-B the de facto standard for evaluating text similarity methods in natural language processing. I remove the 1,363 sentence pairs with some kind of data entry issue (e.g., missing scores and other anomalies) so that the final sample contains $N = 7,182$ sentence pairs.

A.2 Candidate Similarity Functions

I evaluate five embedding-based cosine-similarity models and two frontier large language models (LLMs). All similarity scores are normalized to $[0, 1]$ by dividing human scores by 5 and using cosine output for embedding models (for which the negative scores are collapsed to 0 to match the semantic fields of the original dataset, so the score falls in $[0, 1]$ as for the normalized human scores).

Embedding models:

- *MPNet (local)*: Sentence-BERT all-MPNet-base-v2 (?), open-source, runs locally at zero marginal cost.
- *OpenAI E3 Large*: text-embedding-3-large, 3,072 dimensions, commercial API.
- *OpenAI E3 Small*: text-embedding-3-small, 1,536 dimensions, lower-cost variant.
- *Voyage Finance 2*: Embedding fine-tuned to financial text, Voyage AI API.
- *Voyage 3 Large*: General-purpose embedding, Voyage AI API.

LLMs:

- *Claude Sonnet 4.5*: Direct similarity scoring via prompting, Anthropic API.
- *GPT-4.1*: Direct similarity scoring via prompting, OpenAI API.

LLMs serve as an upper bound on what automated methods can achieve at the time of writing, but they are not actually operationally feasible for large corpora of text because scoring cost scales exponentially in the number of sentences (and linearly in the number of pairs: $\sim \$1 - 2$ for 7,182 pairs here, versus $\sim \$0.03$ for embedding models at corpus scale). With 21,771 stories, that's 236,977,335 story comparisons. If the length of the average story is about 10 sentences, that would be almost 24 billion sentence-pairs compared, or \$3.3 million USD and – even with cheaper or open-source models – an extremely long run-time due to the combinatorial structure, bypassed by cosine-similarity-based approaches. Moreover, LLMs are much more blackbox in their scoring practices while embeddings are at least conceptually understandable: sentences are mapped to a high-dimensional vector space and the cosine of the angle between them reflects their similarity.

A.3 Horse-race Design

The narrative pipeline applies a dead-zone that maps similarity scores below a threshold to zero, treating them as uninformative:

$$D(x) = \begin{cases} 0, & |x| \leq 0.5 \\ x, & |x| > 0.5. \end{cases} \quad (1)$$

I apply $D(\cdot)$ to both the normalized human score $h/5$ and to every model score before computing any error metric. This ensures that every metric reflects the exact transformation the main analysis imposes. (The analysis is stable across some changes of the threshold.)

Data samples. I use complementary samples designed to isolate different aspects of performance.

1. *Full sample* ($N = 7,182$): this data shows how well each method reproduces the global ranking of human similarity judgments, and confirms that embedding-based methods are essentially statistically indistinguishable by conventional metrics on the full data.
2. *Human-active subsample* ($N = 4,101$, human score > 2.5): the set of non-dead-zoned sentence-pairs, as evaluated by humans. This is the main data subset of interest: it measures machine scoring accuracy precisely on the set of sentence-pairs on which the scores are most important.
3. *Both-active subsample*: pairs where *both* the human benchmark and the model classify the pair as outside the dead-zone. This data subset measures within-active-region accuracy after conditioning on the model’s own selection decision, together with precision (share of model-active pairs that are also human-active) and recall (share of human-active pairs captured by the model).

Ranking measures.

- Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n} \sum_{i \in \{\text{all sentence pairs}\}} |s_{\text{model},i} - s_{\text{human},i}|$$

- Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i \in \{\text{all sentence pairs}\}} (s_{\text{model},i} - s_{\text{human},i})^2}$$

- Quadratic Weighted Kappa (QWK):

$$\text{QWK} = 1 - \frac{\sum_{i,j} w_{ij} O_{ij}}{\sum_{i,j} w_{ij} E_{ij}} \quad \text{where } w_{ij} = (i - j)^2 / (N - 1)^2$$

for N the number of distinct classification values.

- Matthews Correlation Coefficient (MCC):

$$\text{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

for TP, TN, FP, FN representing the number of true positives, true negatives, false positives, and false negatives, respectively.

For a separate check, I construct a quintile ordering defined by the quintiles of the *positive* human-score distribution (cut-offs at 0.60, 0.68, 0.80, and 0.88 on the $[0, 1]$ scale), and, separately, a zero-bucket for all pairs with $D(h/5) = 0$. The same human-derived cut-offs are applied unchanged to every model. I report QWK, exact-class accuracy, and the Matthews Correlation Coefficient (MCC) on the full sample using this scheme.

A.3.1 Results

Results are reported in Table A.1.

Panel A: Global performance is similar across embedding methods. On the full sample, rank and scale correlations with human scores are nearly identical across the four strongest embeddings. Spearman correlations range from 0.839 to 0.853 and Pearson correlations from 0.819 to 0.867 among embedding models, while the LLMs attain a slightly higher correlation score (GPT: Spearman 0.888, Pearson 0.886). OpenAI E3 Large achieves the highest R^2 among embedding models (0.751), marginally above MPNet (0.750) and E3 Small (0.747). The near-indistinguishability of the top embedding models on conventional full-sample metrics motivates examining the operationally relevant subsamples in the subsequent panels.

	MPNet	Voyage Finance 2	Voyage 3 Large	OpenAI E3 Small	OpenAI E3 Large	Claude Sonnet 4.5	GPT-4.1
<i>Panel A. Full-sample performance (N = 7,182)</i>							
Spearman ρ	0.853	0.853	0.839	0.846	0.848	0.876	0.888
Pearson ρ	0.866	0.853	0.819	0.864	0.867	0.860	0.886
R^2	0.750	0.728	0.671	0.747	0.751	0.740	0.786
<i>Panel B. Human-active subsample (N = 4,101, human score > 2.5)</i>							
MAE	0.113	0.105	0.131	0.102	0.105	0.129	0.156
RMSE	0.158	0.139	0.160	0.135	0.141	0.173	0.219
<i>Panel C. Both-active intersection (human > 2.5 & model > 0.5)</i>							
N	3,997	4,059	4,097	4,060	4,042	3,989	3,805
MAE	0.101	0.100	0.131	0.097	0.098	0.116	0.121
RMSE	0.127	0.126	0.160	0.122	0.121	0.144	0.152
Precision	0.769	0.718	0.617	0.739	0.749	0.792	0.880
Recall	0.975	0.990	0.999	0.990	0.986	0.973	0.928
<i>Panel D. Ordinal agreement — deadzone + human quintile classes (N = 7,182)</i>							
QWK	0.709	0.673	0.474	0.682	0.702	0.696	0.734
Accuracy	0.445	0.393	0.216	0.418	0.426	0.437	0.516
MCC	0.310	0.266	0.102	0.290	0.295	0.303	0.375
<i>Panel E. Computational requirements</i>							
N (full sample)	7,182	7,182	7,182	7,182	7,182	7,182	7,182
N (both-active)	3,997	4,059	4,097	4,060	4,042	3,989	3,805
Input Tokens	–	245,228	208,609	204,279	204,279	382,955	345,574
Runtime (s)	332	65	87	75	140	104	766
API Cost (\$)	\$0.00	\$0.03	\$0.04	\$0.00	\$0.03	\$2.05	\$1.17

Notes: All scores normalized to $[0, 1]$ before applying the one-sided deadzone $D(x) = 0$ if $|x| \leq 0.5$, $D(x) = x$ otherwise, mirroring the narrative pipeline. Panel A uses raw (non-dead-zoned) scores; Pearson and R^2 are from OLS of human score on model score. Panel B restricts to pairs where the human score exceeds 2.5 (the non-dead-zone region) and reports errors between $D(\text{model})$ and $h/5$. Panel C reports the intersection of non-dead-zone human and model pairs; Precision = share of non-dead-zone model pairs that are also non-dead-zone human; Recall = share of non-dead-zone human pairs captured by the model. Panel D assigns each observation to one of six classes: class 0 (deadzone, $D(h/5) = 0$) and classes 1–5 defined by quintiles of positive human scores (cutoffs at 0.60, 0.68, 0.80, 0.88); model classes use the same human-derived cutoffs. LLMs are included as an upper bound; they are not feasible for large corpora. MPNet runs locally at zero marginal cost.

Table A.1: Horse-Race: Similarity Function Evaluation

Panel B: E3 Large leads among embeddings where it matters. Restricting to pairs where the human benchmark assigns meaningful similarity (human score > 2.5 , $N = 4,101$) substantially reorders the ranking. OpenAI E3 Large achieves an MAE of 0.105 and RMSE of 0.141 on the $[0, 1]$ scale, the best MAE among API embeddings and closely matched only by OpenAI E3 Small (MAE 0.102, RMSE 0.135). Voyage Finance 2 ties E3 Large on MAE (0.105) but has lower RMSE (0.139). The performance of MPNet is slightly weaker (MAE 0.113) despite good full-sample performance.

Interestingly, both LLMs perform worse than the best embeddings on this panel: GPT obtains an MAE of 0.156 and RMSE of 0.219, and Claude an MAE of 0.129 and RMSE of 0.173. This reversal arises because LLMs are too likely to issue “conciliatory” scores, which then map to dead-zones: for instance, 39.8% of GPT’s scores map to, compared to 24.9% for E3 Large.

Embeddings, by contrast, are more uniform in their scoring, hence less heavily penalized by the dead-zone, and, therefore, have lower error in the region of interest.

Panel C: Both-active intersection confirms the ranking with tighter N. For sentence-pairs where both the human benchmark and the model score the pairs as outside the dead-zone, OpenAI E3 Large again achieves the best RMSE of any model (0.121), marginally ahead of E3 Small (0.122) and the two Voyage embeddings (0.126–0.160), but well below the LLMs (Claude 0.144, GPT 0.152). The “accuracy” share of model-retained pairs that are also human-active is 74.9% for E3 Large, compared to 76.9% for MPNet and 88.0% for GPT. The “recall” share of human-scored above-dead-zone pairs that the model correctly identifies as such is 98.6% for E3 Large, meaning it discards fewer than 1.5% of genuinely similar pairs; GPT, for instance, has a 7.2% miss rate. (Voyage 3 Large retains nearly all pairs regardless of human score (99.9% recall, 61.7% accuracy): it is indiscriminately generous in its scoring.)

Panel D: Ordinal agreement corroborates the continuous findings. In the human quintile ordinal classification, E3 Large achieves a QWK of 0.702, the second-highest among embeddings behind MPNet (0.709) and consistent with a decent level of ordinal agreement with human scores. Voyage 3 Large collapses to QWK 0.474: it indiscriminate scoring conflates quantiles. GPT attains the highest QWK overall (0.734); it outperforms on full-sample analyses but not on the high-score-subsample.

Panel E: Cost and feasibility. Processing the full evaluation sample of 7,182 pairs cost \$0.03 for E3 Large (204,279 input tokens at batch API pricing), compared to \$2.05 for Claude and \$1.17 for GPT. At the scale of the main analysis, which involves orders of

magnitude more text pairs than this benchmark, LLM-based scoring is prohibitively expensive. (Moreover, at the time of writing, Claude supports timestamped model API calls, so at least the same model can be used repeatedly, while GPT does not. So, if a GPT model is updated, a researcher cannot directly access an older one for data reproducibility.) Among embedding models, E3 Small is marginally cheaper (\$0.004) and slightly faster (75s vs. 140s) but offers no consistent accuracy advantage over E3 Large across the panels. MPNet incurs zero marginal cost.

A.3.2 Conclusion

Taken together, these analyses support selecting OpenAI E3 Large as the similarity function for the main analysis. Full-sample evidence places it in an effective tie with MPNet and E3 Small. On the high human score subsample and high human and model score subsamples E3 Large is consistently among the two most accurate embedding models on continuous error metrics, achieves the best RMSE in the intersection, and maintains near-perfect recall. It is also the best-performing API embedding on R^2 (0.751) across the full sample. It approaches the performance of frontier LLMs without the financial or compute costs.

B Narrative-Extraction Methodology In Greater Depth

B.1 Story extraction from news articles

The theoretical model remains agnostic as to the provenance of stories. Entries in a data set can already be structured as stories, or may require some transformation. The extraction of stories in this paper is performed by an LLM on the basis of news articles, but one can readily imagine different sources: (ordered) responses to open-ended decision-questions posed in an experiment, testimony or survey evidence, speeches, earnings calls, social media posts, and so forth. There are no hard constraints on the text inputs which can be used, but shorter texts work better than long texts due to computational complexity, and the plausibility of unresolvable temporal nonlinearities and contradictions in longer texts.¹

¹A nonlinearity in the text is resolvable as long as the implied linear chronological order can be recovered. The fact that many news articles contain explicit flashback-like references to past facts – or are even written in reverse chronological order – does not pose a problem because the implied order is easily recoverable. A book containing several stories unfolding in parallel, or discussing contradictory or counterfactual explanations of the same historical phenomenon, does not lend itself to this structure, however. In some cases, it may be possible to address this issue by passing to smaller sections of texts (e.g., chapters), until each block of text can be reduced to a single story.

Every individual text is processed using Claude Sonnet 4.5 (timestamped to 2025-09-29 and with temperature [stochasticity] set to zero for maximal replicability; in memory-less, independent fashion, à la i.i.d. draws) with a prompt (provided in the Appendix) designed to extract each article’s story – the list of facts best summarizing the article – along with a few extra variables, such as keywords and newspaper country of origin.² Each fact is a single sentence (subject-verb-complement). I also maintain a record of whether the fact is a realized event and or forecasted prediction, and obtain a representation of each fact’s informational contents along the who-what-where-when-why-how axes.³

B.1.1 Prompts

Story-Extraction Prompt The following, in its entirety, is the full prompt provided to the LLM to summarize articles into stories. *Please read the following article and extract the relevant information. Return your report as a JSON object in the following format:*

```
{
  "title": "[title of article]",
  "date": "[date of article publication in YYYY-MM-DD]",
  "author": "[article author]"
  "keywords": "[key words]",
  "sequence of events": ["[event 1]", "[event 2]", ...],

  "event 1 who": "[who is the agent/actor/participant in event 1]",
  "event 1 what": "[what is happening in event 1]",
  "event 1 where": "[where event 1 occurred]",
  "event 1 when": "[when event 1 occurred]",
  "event 1 why": "[why event 1 occurred]",
  "event 1 how": "[how event 1 occurred]",

  "event 2 who": "[who is the agent/actor/participant in event 2]",
  "event 2 what": "[what is happening in event 2]",
  "event 2 where": "[where event 2 occurred]",
  "event 2 when": "[when event 2 occurred]",
  "event 2 why": "[why event 2 occurred]",
```

²These other variables make for useful controls in the empirical analysis; they are not part of a story’s structure.

³The LLM is taken “off-the-shelf” and can be easily replaced with another (e.g., a free, open-source model, or a specially-tuned one), or even human-generated structured responses.

```

"event 2 how": "[how event 2 occurred]",
....
"event i who": "[who is the agent/actor/participant in event i]",
"event i what": "[what is happening in event i]",
"event i where": "[where event i occurred]",
"event i when": "[when event i occurred]",
"event i why": "[why event i occurred]",
"event i how": "[how event i occurred]",

"predictions": ["[prediction 1 made by article]", "[prediction 2]", ...],

"prediction i who": "[who is the agent/actor/participant in prediction i]",
"prediction i what": "[what will happen in prediction i]",
"prediction i where": "[where prediction i will occur]",
"prediction i when": "[when prediction i will occur]",
"prediction i why": "[why prediction i will occur]",
"prediction i how": "[how prediction i will occur]",

}

```

Your goal is to extract the story structure of the article. Please respect the following constraints:

- *Include only the events and predictions most important to understanding the story contained in the article. Be highly selective.*
- *For each event, event = who + what + when + where + why + how. You must include information from ALL sub-fields in the event. There should be NO information in the event breakdown not included in the event description.*
- *Make sure that there is a logical, narrative flow of event i to event $i + 1$, and likewise for predictions.*
- *Use active voice only. There should be no passive voice anywhere.*
- *Record events in the order in which they occur in the real world (which may be different from the order in the article). Simultaneously-occurring events should be condensed into the same event.*
- *“When” can be given in relative time (e.g., “two weeks after event $i - 1$ ”) if need be.*

- *“Why” provides the stated cause. “How” provides the stated method or mechanism.*
- *If any information is not explicitly stated, write “NA” for the corresponding field.*

Include detailed information and format the JSON correctly. Include only the JSON and do not include any other text.

Please analyze the following article:

[article text]

B.2 Story comparisons

B.2.1 Fact comparisons: Interpreting the fact-wise similarity function

There are several interpretations possible for such a function. One can think of it as capturing the analyst’s perception of semantic similarity, or as reflecting a normative standard for semantic similarity of which all individuals could be eventually persuaded.⁴ Finally, the preferred interpretation in this paper – not mutually exclusive with the interpretations proposed earlier – is that of an average notion of similarity: suppose that a population is asked to report their (subjective) similarity functions; an average is taken, and a population similarity function is obtained. Indeed, the empirical implementation of the similarity function, which uses embeddings, exploits similarity notions distilled from very large (quasi-population-level) training data, thus arguably reflecting a population-level average.⁵

B.2.2 Story comparisons: alignment optimization implementation

I compute the optimal alignment score algorithmically using dynamic programming. Direct construction of the optimal alignment itself would be combinatorially explosive and infeasible with a dataset of non-trivial size. Instead, for two stories of lengths m and n I build an $m \times n$ matrix whose entries are pre-computed cosine similarities between corresponding facts, then recover an optimal alignment by dynamic programming in $O(mn)$ (polynomial) time. The DP algorithm maximizes cumulative similarity under a three-way recurrence: match the current facts, skip a fact on the first story, or skip on the second story. Terminal states of the DP algorithm are determined by the positions of first and last facts of both stories, and the number of matches. These positions and number of matches are exactly the information required to calculate the density penalty, governed by the parameter α , which is then applied to each of the retained raw scores in the final optimization step. The algorithm returns the “winning” terminal state by selecting the highest raw score $\times$ alignment-specific density penalty product. (See B.1 for alignment score distributions based on different choices of α .)

Is a match with zero-similarity a real match? The choice of optimal alignment reflects a trade-off between total score maximization and a penalty associated to “skipping” over

⁴That is, two people might disagree on the similarity of two sentences, for instance due to gaps in vocabulary or connotation, but one should be able to persuade the other, insofar as assessment of similarity of sentences is an intellectual exercise distinct from assessment of agreement with the substance thereof.

⁵Further consistent with this interpretation, an embedding-free implementation of the proposed methodology would consist of employing several human subjects, asking them all to score the similarities, and in using the average of the provided scores – lest some outlier or error bias results.

facts – or, in other words, between the quality and number of matches. Counting as valid the matching of two facts with zero-similarity would make the aforementioned trade-off trivial. To maintain its non-triviality, therefore, the algorithm explicitly rules out this case: to match two facts, their similarity must be non-zero; otherwise, one of them must be skipped. (This consideration lends a conceptual advantage to the “dead-zone” around zero introduced in the embedding-based similarity. It is conceptually useful for there to be a discontinuity – to make the trade-offs meaningful – and for this discontinuity to be applied not as a singularity but on an interval around zero.) The default dead-zone in the algorithm, and the one used in the paper, is $[-0.5, 0.5]$.

B.2.3 Choice of density penalty severity parameter α

The analyst is free to choose the α he considers most appropriate for his application. One possible criterion – and the one I use to fix $\alpha = 0.1$ – is based on defining when a “skip” of an event would and would not be allowed. In particular:

- *Do* skip one event if improves match quality by 1 s.d. in median case;
- *Do not* skip two events if it improves match quality by 1 s.d. in median case.

$$\begin{aligned}
 (\text{prev. total} + \text{score}_H) \left(\frac{\# \text{matches} + 1}{\# \text{matches} + \# \text{padding} + 2} \right)^\alpha &> \\
 &(\text{prev. total} + \text{score}_L) \left(\frac{\# \text{matches} + 1}{\# \text{matches} + \# \text{padding} + 1} \right)^\alpha \\
 (\text{prev. total} + \text{score}_H) \left(\frac{\# \text{matches} + 1}{\# \text{matches} + \# \text{padding} + 3} \right)^\alpha &< \\
 &(\text{prev. total} + \text{score}_L) \left(\frac{\# \text{matches} + 1}{\# \text{matches} + \# \text{padding} + 1} \right)^\alpha
 \end{aligned}$$

plugging in the median event-pair scores, typical number of matches (if unconstrained), $s_H - s_L = 1$ s.d..

With the numbers in the Factiva-based Liberation Day data set, $\alpha = 0.1$ is squarely within the middle of the interval by the above criterion and near its midpoint. Moreover, $\alpha = 0.1$ is robust to the use of the min instead of the median in the above calculation. (See B.1 for alignment score distributions based on different choices of α .)

B.2.4 Robustness to Choice of α

See Figure B.2 for stability tests across α using Jaccard matrices based on top 2% of story-scores, and top-20 and top-100 narrative communities, as well as a Spearman rank corre-

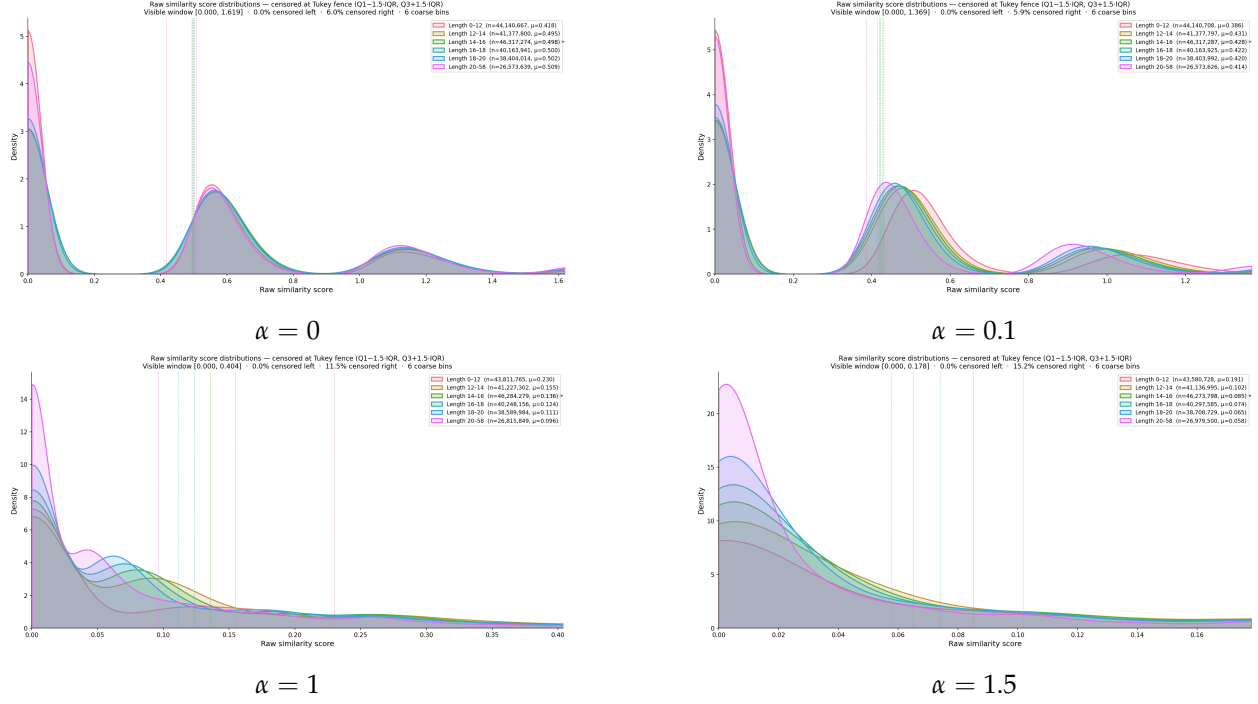


Figure B.1: Optimal Alignment Scores with Different α

lation matrix.

B.2.5 Axiomatization of the Alignment Score

The alignment score – which evaluates the similarity of two stories conditional on a given alignment as the sum of similarities of the induced fact-pairs – is axiomatized as follows. Let $\succeq \subset \mathcal{J}(\mathcal{Q} \times \mathcal{Q}) \times \mathcal{J}(\mathcal{Q} \times \mathcal{Q})$ denote the binary relation representing similarity between stories conditional on alignment. As alignments determine fact-pairs are compared, similarity must necessarily be defined relative to an alignment, and cannot be intrinsic to a particular fact or story.

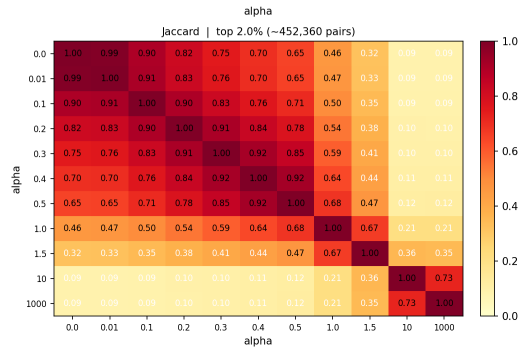
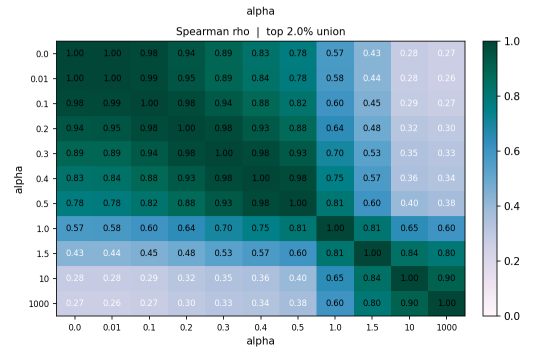
First, I'll assume a form of permutation invariance to ensure that constituent facts are being compared without reference to order.

Axiom 1 (Permutation Invariance). For any pair of stories q_1, q_2 , any alignment j thereof, and any bijection $\pi : \{1, \dots, \text{len}(j(q_1, q_2))\} \rightarrow \{1, \dots, \text{len}(j(q_1, q_2))\}$,

$$j(q_1, q_2) \sim_{\triangleright} \pi(j(q_1, q_2))$$

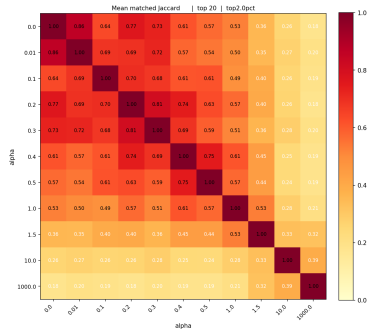
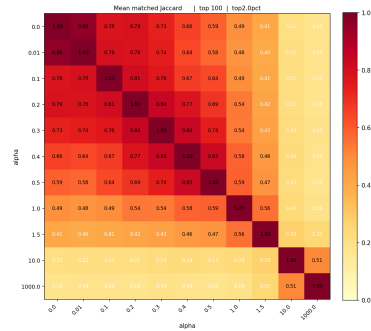
where $\pi(j(q_1, q_2))$ denotes the alignment obtained by permuting the entries according to π .

Permutation invariance justifies representing an alignment by its support, as repre-



Jaccard: Top 2% Story-Scores
Community robustness (top2.0pct): stability of top-20 communities across alpha values

Spearman: Top 2% Story-Scores
Community robustness (top2.0pct): stability of top-100 communities across alpha values



Jaccard: Top-20 Narratives

Jaccard: Top-100 Narratives

Figure B.2: Robustness to Different Choices of α

sented by a fact-pair counting function $I_{j(q_1, q_2)} : \mathcal{F} \times \mathcal{F} \rightarrow \mathbb{Z}_{\geq 0}$,

$$I_{j(q_1, q_2)}((f_1, f_2)) = \#\{i : j(q_1, q_2)_i = (f_1, f_2)\}$$

since any ordering of the same collection of fact-pairs is equivalent for evaluation.

Let $P = \mathcal{F} \times \mathcal{F}$ represent all possible fact-pairs and $\mathcal{I} = \{I : P \rightarrow \mathbb{Z}_{\geq 0} \mid \sum_{p \in P} I(p) < \infty\}$ be the set of all (finite-support) fact-pair counter functions for all possible alignments of all possible stories. All operations on $\mathcal{I}$ are performed point-wise. Let $\succsim \subset \mathcal{I} \times \mathcal{I}$ be the representation of the similarity of stories, conditional on alignment, equivalent to that induced by $\triangleright$. Let $\sim$ and $\succ$ denote the symmetric and asymmetric parts of $\succsim$, respectively.

Axiom 2 (Weak Order). $\succsim$ is complete and transitive

(Any two alignments of story pairs can be compared.)

Axiom 3 (Union). For all $I, J, K \in \mathcal{I}$, $I \succsim J \iff I + K \succsim J + K$

(Adding the same multiset of fact-pairs to two alignments should not change their ranking.)

Axiom 4 (Archimedeanity). For all $I, J, K, L \in \mathcal{I}$,

$$I \succ J \implies \text{there exists } n \geq 0 \text{ such that } I + nK \succ J + nL.$$

(There are no infinitely similar or dissimilar alignments.)

The desired representation follows immediately from an adaptation of Theorem 2 of Rusonik (R Samuelson (Gilboa (2026)):

Theorem 1 (Rusonik (R Samuelson (Gilboa (2026))). $\succsim$ satisfies A2-A4 iff there exists a function

$$s : (\mathcal{F} \times \mathcal{F}) \rightarrow \mathbb{R}$$

such that, for all $I, J \in \mathcal{I}$

$$I \succsim J \iff \sum_{p \in P} I(p) s(p) \geq \sum_{p \in P} J(p) s(p)$$

Moreover, in this case s is unique up to multiplication by a positive number.

To have the similarity function map to $[-1, 1]$, and for $s = -1, 0, 1$ to denote opposite, orthogonal, and identical meaning, respectively, a technical rescaling axiom is required:

Axiom 5 (Normalization). For any facts $F, F' \in \mathcal{F}$, there exist facts $\neg F, \neg F' \in \mathcal{F}$ such that

$$\mathbb{1}(F, F) + \mathbb{1}(F, \neg F) \sim \mathbb{1}(F', \emptyset) \sim \mathbb{1}(\emptyset, \emptyset) \sim 0 \quad (2)$$

$$\mathbb{1}(F', F') \sim \mathbb{1}(F, F) \succsim \mathbb{1}(F, F') \succsim \mathbb{1}(F, \neg F) \sim \mathbb{1}(F', \neg F') \quad (3)$$

where $0 \in \mathcal{I}$ is the zero counter function (empty alignment) and the weak relations in (2) are strict whenever $F \neq F'$.

The above means that the range of s is a closed interval centred at 0 ; without loss of generality, it can be normalized to $[-1, 1]$.

Remark. $d : \mathcal{Q} \times \mathcal{Q} \rightarrow \mathbb{R}_{\geq 0}$ defined by $d(q_1, q_2) = \min_{i=1,2} \{\text{len}(q_i)\} - V(q_1, q_2)$ induces a semimetric over the space of stories. (A semimetric satisfies all axioms of a metric – non-negativity, identity of indiscernibles, and symmetry – except for the triangle inequality, which is not desirable in this context: a comparison of a pair of long, very different stories to third, very short story, will always yield small(er) distances.)

B.3 Narrative clustering

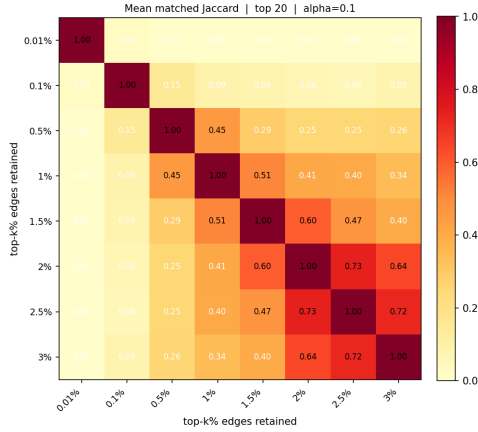
B.3.1 Retaining Edges and robustness to different settings

For bins created by optimal alignment length for each story-pair, I standardize the similarity scores. I retain the top 2% of edges with scores with z-score above 1.28 are plotted⁶, which is about the top .2% overall of edges overall. With these scores interpretable as measures of exceptional similarity of story-pairs, we can directly apply the Leiden community detection algorithm (Traag et al., 2019).

For reasons of computational tractability and interpretable outcomes, it is not possible to retain all edges. Importantly, even if it were computationally feasible, it would not be economically desirable to keep all edges. This is the Leiden algorithm interprets the very presence of an edge as a sign of similarity and – with standardized scores all somewhat close together – has difficulty parsing which edges ought to be kept. In other words, retaining all edges artificially inflates the perceived similarity of all stories and makes it difficult for the algorithm to recover truly meaningful communities. Under such a configuration, false positives of similarity (whereby stories get treated as similar when, in fact, they should not be) are much more likely. Dropping edges preemptively constitutes a computational advantage and makes meaningful outcomes more likely: the Leiden algorithm is forced to look for meaningful clusters given edges that are a true sign of exceptional similarity.

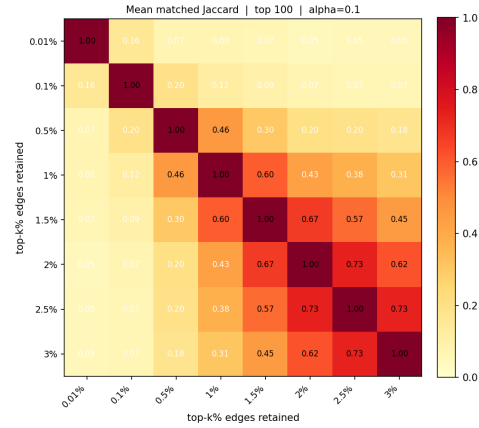
⁶Cantelli’s inequality guarantees that the retained scores are in the top 40% of distribution.

Community robustness (alpha=0.1): stability of top-20 communities across top-k% edge thresholds



Jaccard: Top 20 communities

Community robustness (alpha=0.1): stability of top-100 communities across top-k% edge thresholds



Jaccard: Top 100 communities]

Figure B.3: Robustness to different top-% shares retained

However, the decision of which share of edges should be dropped is not an obvious one, and there is no obvious rational threshold to apply as with the choice of α . In what follows, I present results to show that

B.3.2 How many narratives to retain?

I retain the top 14 narratives by size, and collapse all others into a catch-all category for all other tariff-related narratives. The fourteen are chosen because (i) each has at least 200 news articles (just under 10% of the max largest community), and (ii) cumulatively their coverage is over 50% of all included articles. The distribution is shown in Figure B.4.

Figures B.6 and B.7 illustrate that adding more of the smaller communities would not change anything materially, and Figure B.5 presents the top 15 as shares.

B.4 How to characterize narratives

To characterize each narrative (cluster of stories), I deterministically rely on the most representative stories according to two criteria: *centrality* and *coverage*. First, for each community, the algorithm selects the most central stories as measured by eigenvector centrality. Selection stops when either the 50th percentile threshold is reached or 5 stories are selected, whichever comes first. Second, for each community, the algorithm selects stories that maximize network coverage using a greedy algorithm: coverage tracks the total degree of all selected nodes but without double-counting previously-counted neighbours. Selection stops when either 67% coverage is achieved or 5 stories are selected, whichever comes first.

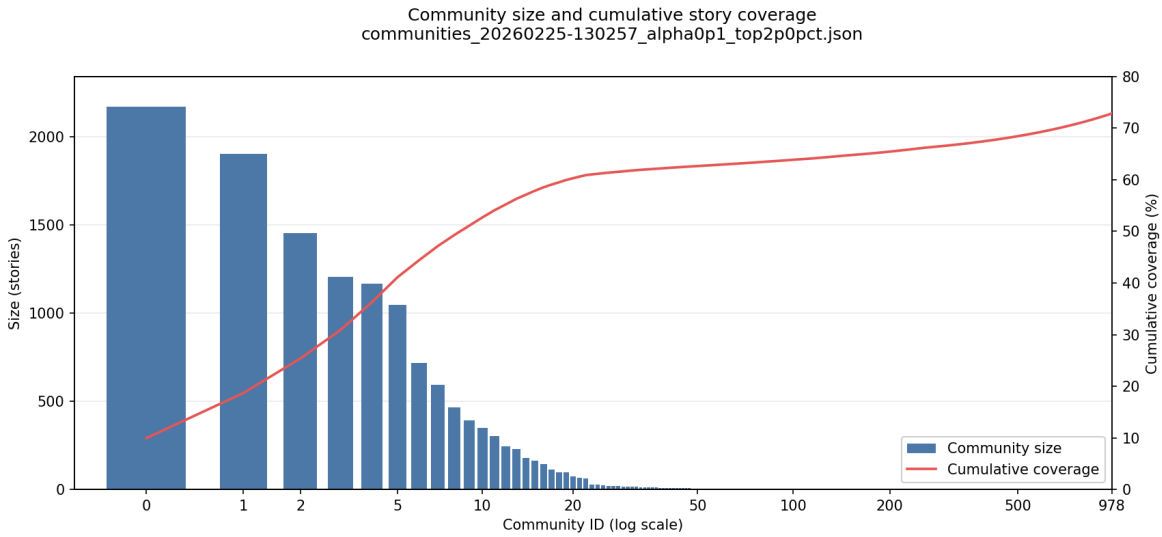


Figure B.4: Narrative size and cumulative coverage

Narrative clusters (communities) are ordered by size, in decreasing order. The cumulative coverage (right y-axis) caps at just over 70% because this graph excludes singletons are excluded. An inverse-logarithmic scale is used on the x-axis to fit all narrative clusters (except singletons).

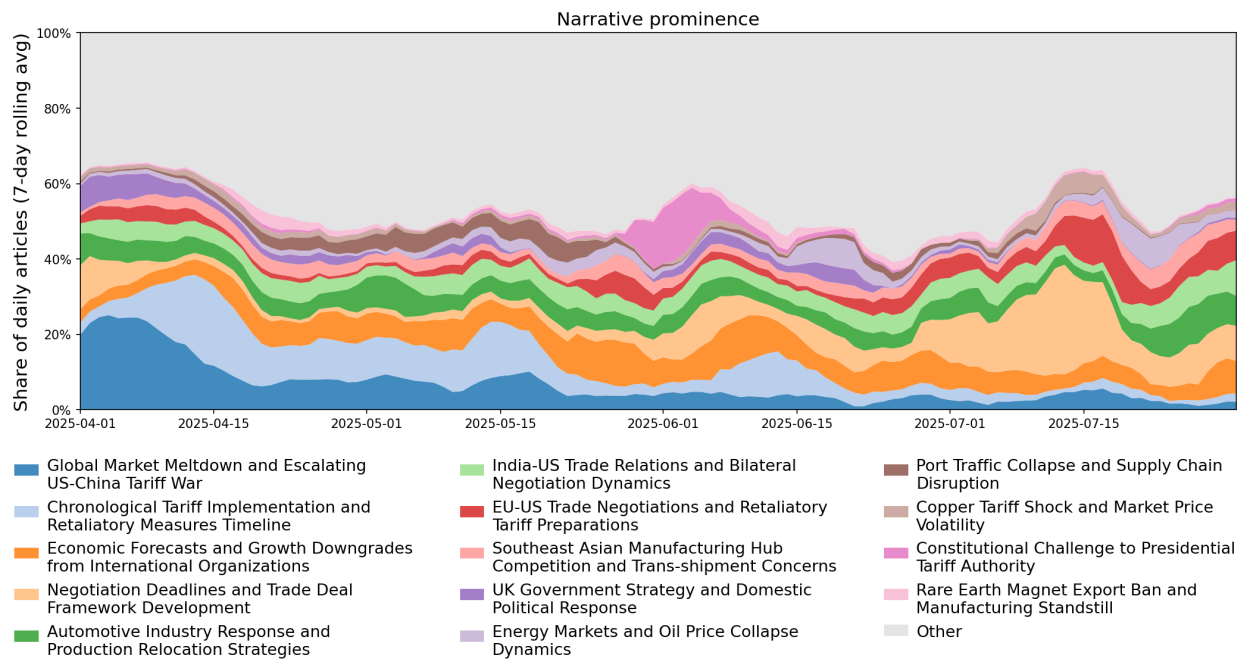


Figure B.5: Top 14+1 narratives by size, presented as shares

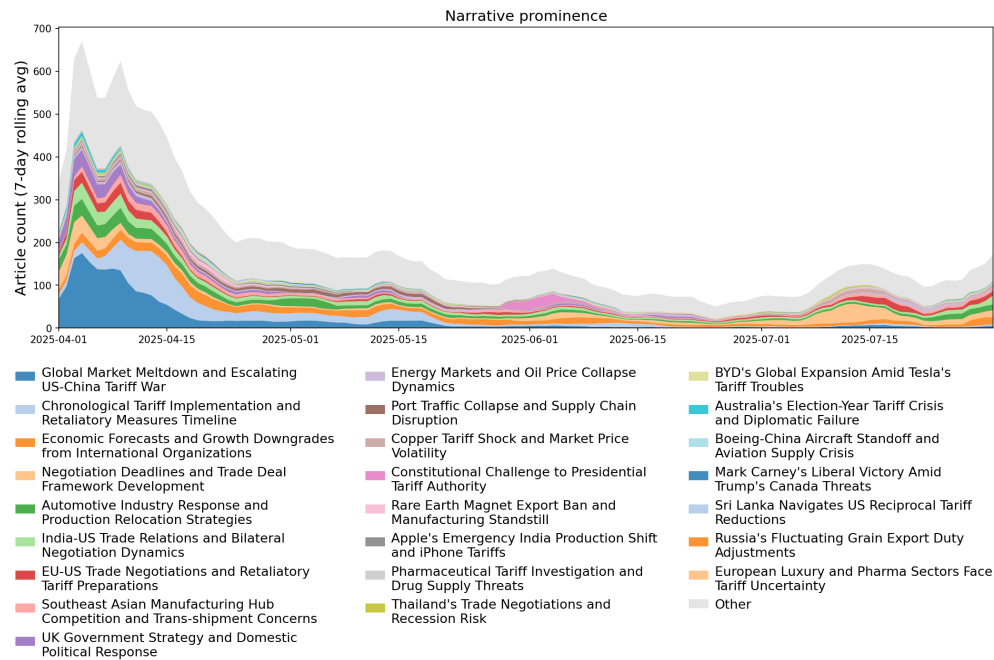


Figure B.6: Top 24+1 narratives by size

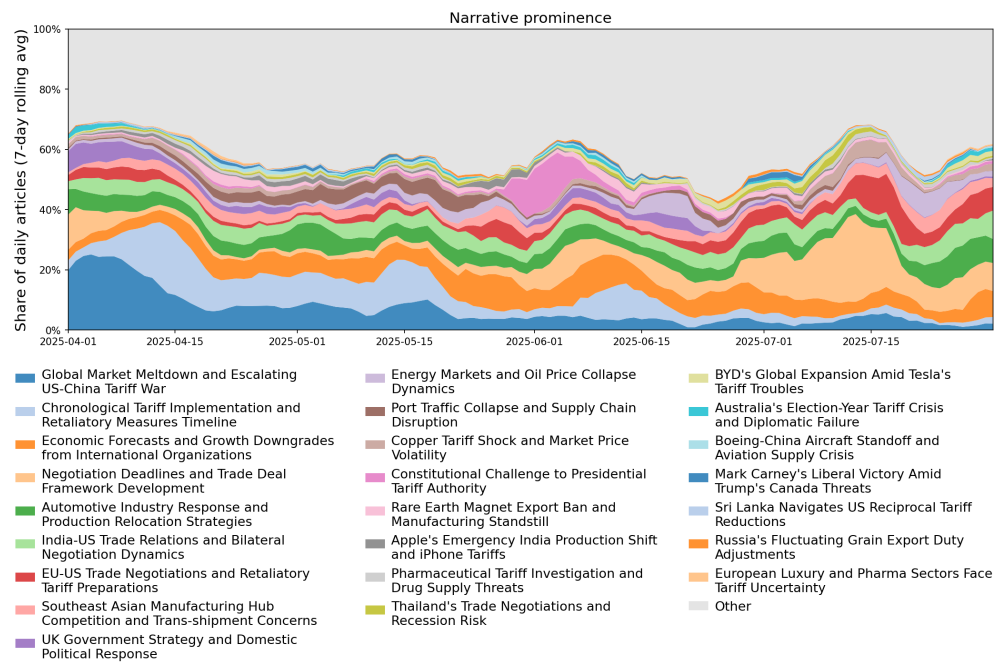


Figure B.7: Top 24+1 narratives by size, presented as shares

These representative stories are deterministic and constitute the characterization of the narrative. For a more readable overview, these representative, characterizing stories in full (including their fact-breakdowns, full texts, etc.) are provided to Claude Sonnet 4.5, which is then asked to give a summary of each narrative based on the narrative’s provided defining stories.

B.5 Extracting Narratives from “Liberation Day”

Data: Newspaper Articles I obtain the full dataset of English-language news articles on Dow Jones Factiva from April 1st - July 31st, 2025, tagged as relating to “Trade Barriers/Restrictions”⁷, from all authors, on all industries and companies, concerning the United States, Canada, Europe, Asia, and the Asia Pacific, from “major new and business sources” from the United States, Canada, Europe, and Asia. In total, there were 21 973 news articles (over 5000 from US sources; over 6000 from the EU; and over 8000 from Asia), of which 21 771 were unique. I retain only the unique articles (as non-uniqueness implies re-publication in another newspaper or perhaps its own online affiliate, but does not bespeak broader readership).

I run the narrative-extraction methodology on these news articles, all pooled together. Figure ?? presents the strequence similarity scores for all story-pairs, grouped by optimal alignment length, with $\alpha = 0.1$. All other settings are maintained as the default. The methodology yields the communities shown in Figure B.9. There are 869 non-singleton narrative clusters, which cover 15 974 news articles, and the remaining 5 797 stories are assigned to singleton narrative clusters. The full set of narrative characterizations is included in Appendix C.

Figure ?? plots each of the top 14 narratives by aggregate size (plus a fifteenth cluster which is a miscellaneous category, pooling the remaining articles) by articles’ publication dates. Throughout the empirical analysis, I work with these 14+1 because the top-14 cover more than 50% of all published articles while remaining few enough in number that analysis is tractable and quantitative models are not over-specified.

Narratives’ size and temporal prominence is consistent with what one might expect. For instance, the largest narrative overall – “Trump’s Escalating Trade War and Global Market Volatility” (dark blue) – is one which emerges very quickly, and then begins to shrink in importance in short order, as would generally be expected of a narrative which serves, primarily, only to announce the arrival of tariffs. The narrative on “Legal Challenges and Methodological Disputes Over Tariff Authority” (magenta) appears in late May with the first court rulings concerning the President’s authority to impose tariffs, and

⁷I query Factiva using its structured metadata filters rather than a free-text keyword restriction: the Text field is left blank, the Subject filter is set to Trade Barriers/Restrictions.

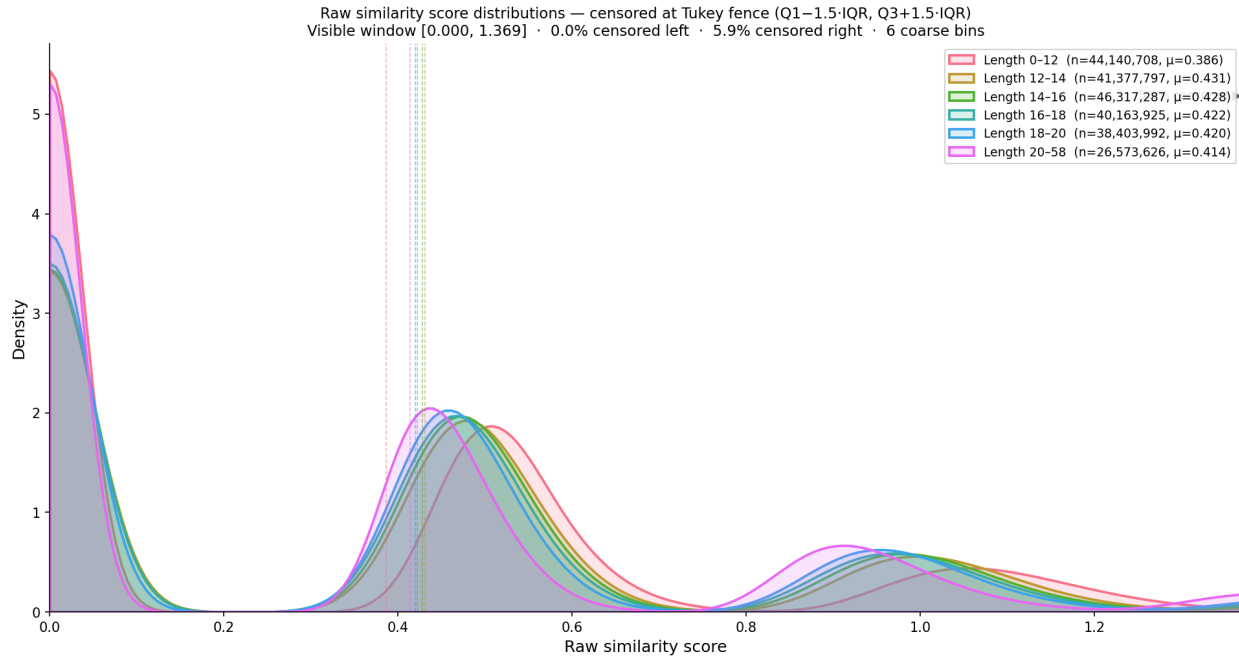
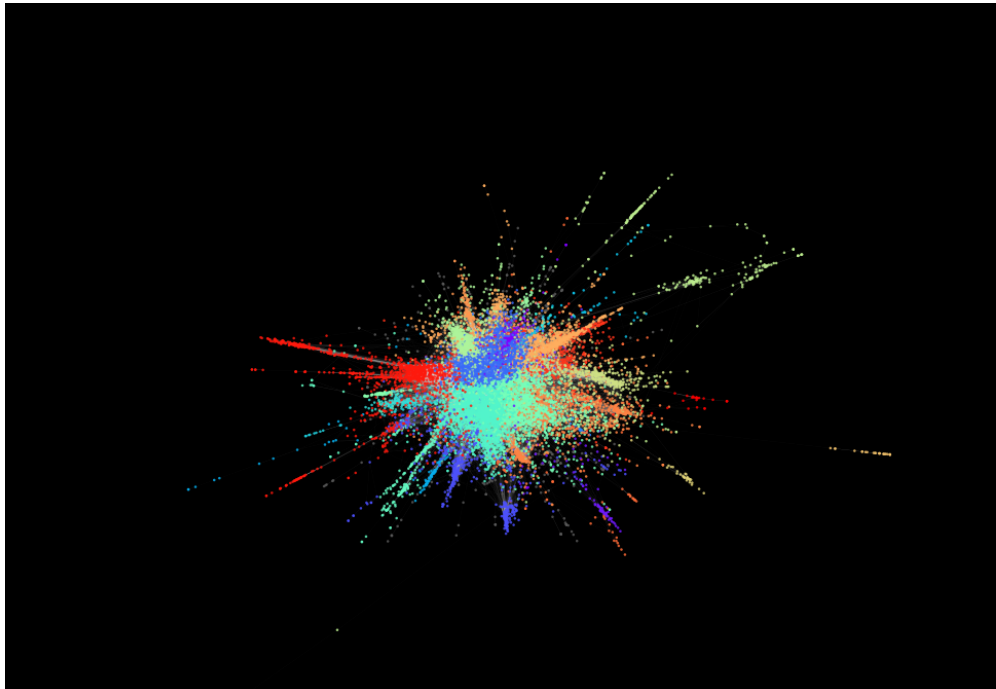


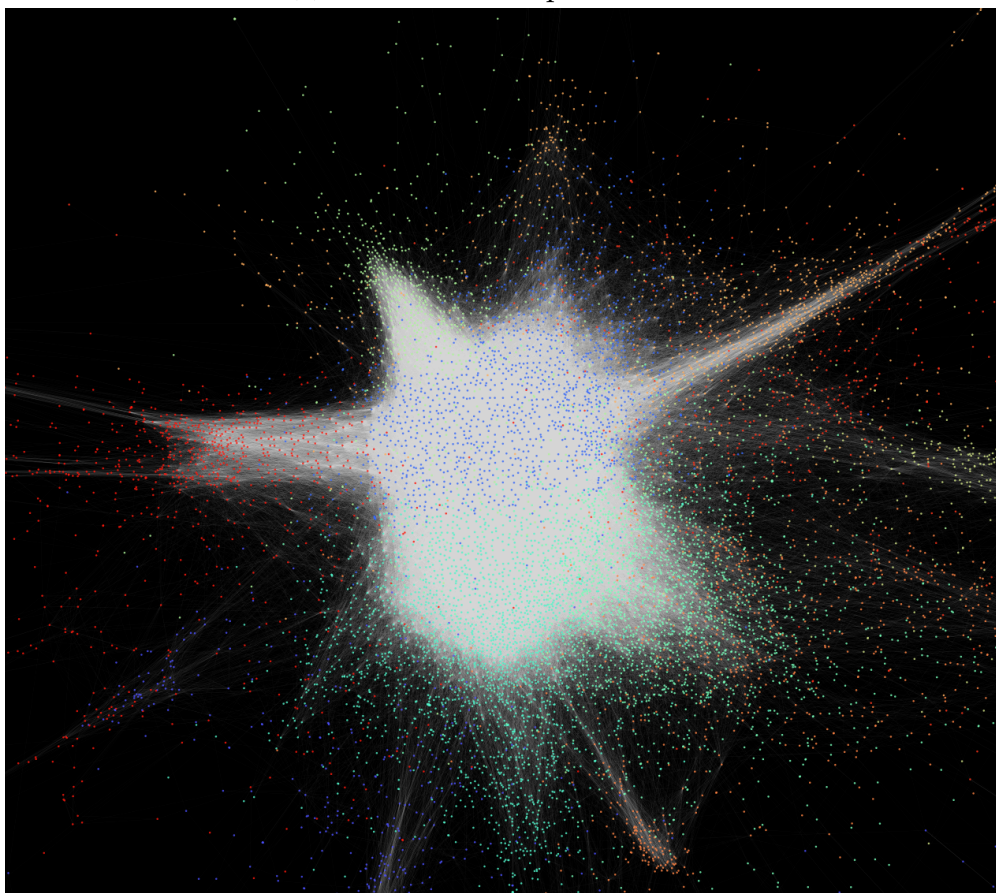
Figure B.8: Strenesse Similarity Scores

vanished by mid-June when temporary stays were granted, allowing the Federal Government to prepare its appeals.⁸ Similarly, the narrative on “European Economic Impact and Trade Deal Negotiation” (golden-orange) and the “EU’s Coordinated Countermeasures and Sectoral Impact Assessment” (crimson), bearing on various aspects of negotiations with the EU, are most salient very early in the tariff discussions, at the time of greatest uncertainty, and at the end of the sample when the negotiations were converging to a resolution. That the emergence and dissipation of narratives coincide with the periods over which one would expect the narratives to be salient is a strong indication of the validity of the method: the clustering identifies meaningful patterns.

⁸The Court of International Trade ruling was handed down on May 28th, labeling the tariffs an unconstitutional overreach of executive power, and temporary stays were granted on May 29th and June 11 to allow tariffs to remain in place while the government prepared its appeals.



(a) All narratives; top 30 coloured



(b) Top 10 coloured

Figure B.9: Narrative Communities

There are 21 771 stories grouped into 869 non-singleton communities (which cover 15 974 stories in non-singleton communities). The top 30 and top 10 largest are colored in the above graphs. Edges between any two dots (stories) are white, and the intensity of the color reflects the score of the edge.

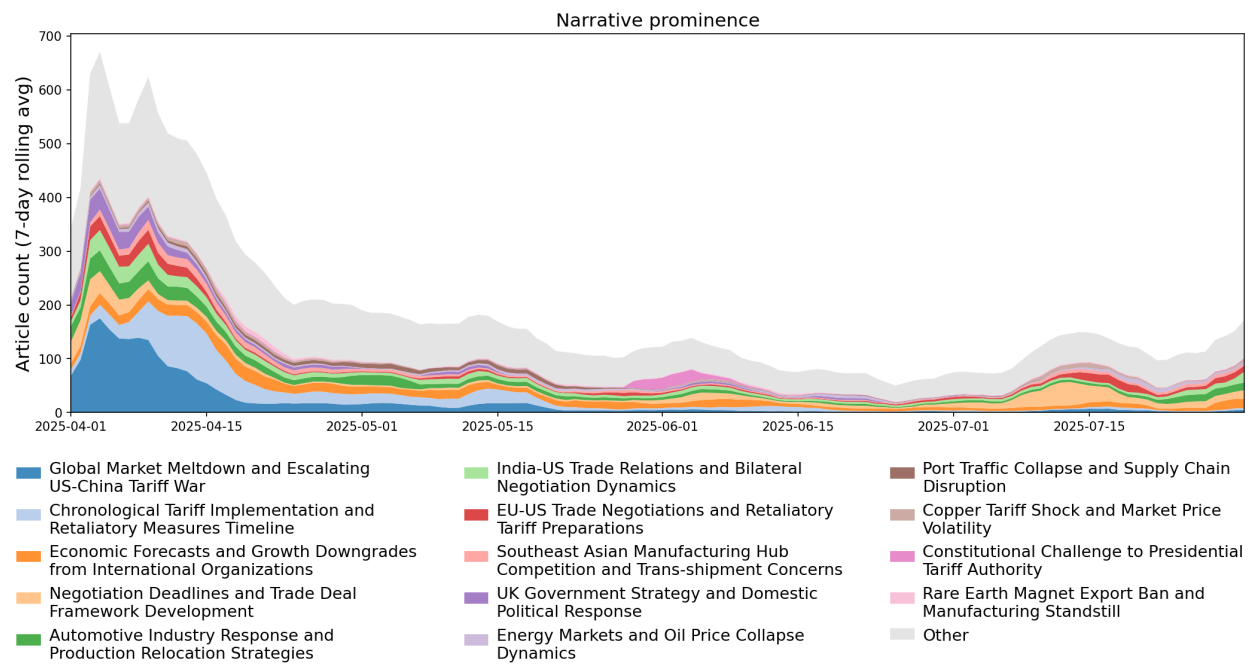


Figure B.10: Narratives Over Time

Each of the 14 largest overall tariff narratives is presented in the graph; the remaining narratives are grouped together into a catch-all “other” narrative. Only narrative titles are shown; for a full characterization of each narrative, see Appendix C.

B.6 Publication Times of the Articles

The corpus contains 21,755 articles published between 1 April and 31 July 2025.⁹ For each article I read the publication date and, when available, the publication time from the Factiva header.

Time zone. Whenever a timestamp is available, Factiva reports the time of every article in US Eastern time, whatever the outlet’s location. While I did not find this listed as official Factiva policy, I have corroborated this in three ways. First, the Dow Jones market-headline digests contain their release time in their titles (“Top Markets Headlines at 9 PM ET”), and for 36 of the 38 such digests the Factiva time falls in exactly that hour. Second, an article from the Korean outlet Yonhap titled “(EDITORIAL from The Korea Times on Aug. 1)” is stamped 31 July 2025 at 18:01, which is 07:01 on 1 August in Korea. Third, Korean and British outlets publish at hours that correspond to their local daytime once the timestamps are read as indicating Eastern time. I therefore use the Factiva date and time as Eastern Time (on which the NYSE operates) for all articles without adjustment, and I treat the header date as the New York date for articles that do not list a time.

Coverage. Table B.1 reports how many articles print a usable time. 41.0% have a time stamp, 58.0% have no time line at all, and 0.8% are stamped exactly 00:00. The 00:00 stamps are concentrated in a few outlets (see Table B.4) and are likely placeholders, data glitches, or articles earmarked to be published the next day rather – and are hence not really true news-release times. Coverage depends almost entirely on the outlet: newswires and online editions are time-stamped, while print editions never are.

Trading hours. I classify each time-stamped article as being published before market open (00:00 to 09:29), during trading hours (09:30 to 16:00 inclusive), or after the close (16:01 onward), relative to the NYSE. On the early-close day of 3 July 2025, the market close is assigned at 13:00. Articles published on weekends and NYSE holidays (Table B.5) are also assigned to closed days and make up 9.8% of all time-stamped articles.

Table B.2 reports the average daily shares over the 84 trading days in the sample. Among time-stamped articles, 31.1% are published during trading hours, 48.7% before the open, and 20.2% after the close, so 79.8% appear before or during the trading session. As a share of all articles, which treats every article without a usable time as falling outside the session, the corresponding figures are 13.3% and 33.8%. These are lower bounds.

⁹These are the articles retained in the story-extraction step. Four further articles are dropped because their raw Factiva text is missing, and twelve because they are dated 31 March 2025.

The imputed column instead assigns every article without a usable time at 00:00 on its publication date.

Figure B.11 and Table B.3 show the average distribution of publication times across the hours of the day. Figure B.12 shows the daily composition of articles by time status and session.

Table B.1: Availability of publication times

Time status	Articles	Share (%)
Time stamp	8,922	41.0
No time line	12,624	58.0
Stamped exactly 00:00	182	0.8
No parsable header	27	0.1
Total	21,755	100.0

All articles in the sample. “No parsable header” are articles whose raw text lacks the Factiva header block.

Table B.2: Share of articles by NYSE session, trading days (%)

	Timed articles	All articles	Imputed
Before the open (00:00–09:29)	48.7	20.5	77.9
During trading hours (09:30–16:00)	31.1	13.3	13.3
After the close (16:01–23:59)	20.2	8.8	8.8
Before or during trading hours	79.8	33.8	91.2

Means of daily shares over the 84 trading days in the sample; times are New York time. “Timed articles”: share of articles with a time stamp (00:00 stamps excluded). “All articles”: same counts divided by all articles published that day; the remainder are articles without a usable time. “Placebo”: articles without a time and articles stamped 00:00 are placed at 00:00 on their publication date. On 3 July 2025 trading ends at 13:00.

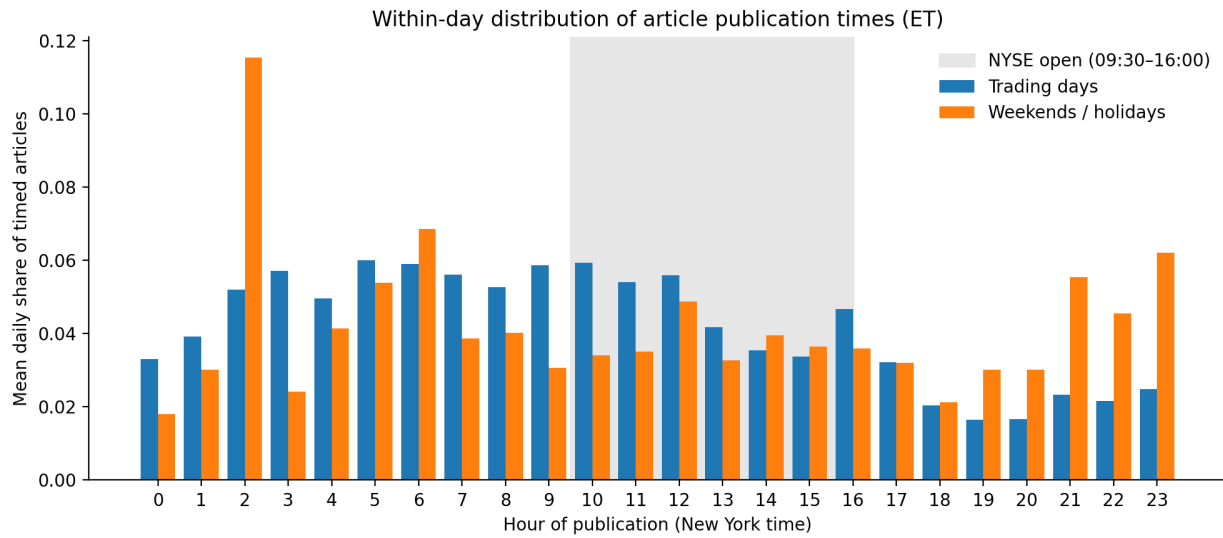


Figure B.11: Within-day distribution of publication times

Mean over days of the share of time-stamped articles published in each hour (New York time), separately for trading days and for weekends and NYSE holidays. The shaded area indicates trading hours.

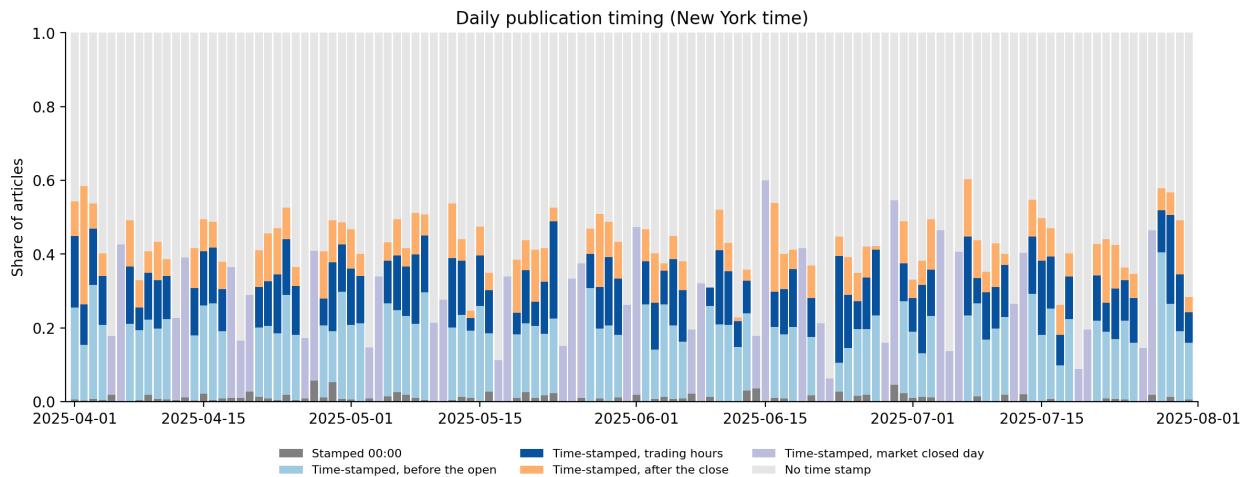


Figure B.12: Daily publication timing

Each bar splits the articles published on a given day (New York time) into: articles stamped exactly 00:00; time-stamped articles published before the open (00:00–09:29), during trading hours (09:30–16:00), or after the close (16:01–23:59); time-stamped articles published on weekends and NYSE holidays; and articles without a time stamp. Bars sum to one.

Table B.3: Hourly distribution of publication times (%)

Hour (ET)	Articles	Pooled	Trading days	Closed days	Placebo
00:00	270	3.0	3.3	1.8	63.1
01:00	353	4.0	3.9	3.0	1.4
02:00	488	5.5	5.2	11.5	2.1
03:00	477	5.3	5.7	2.4	1.9
04:00	436	4.9	5.0	4.1	1.8
05:00	575	6.4	6.0	5.4	2.2
06:00	523	5.9	5.9	6.9	2.3
07:00	491	5.5	5.6	3.9	2.0
08:00	439	4.9	5.3	4.0	1.9
09:00	492	5.5	5.9	3.1	2.0
10:00	502	5.6	5.9	3.4	2.1
11:00	449	5.0	5.4	3.5	2.0
12:00	513	5.7	5.6	4.9	2.1
13:00	354	4.0	4.2	3.3	1.5
14:00	327	3.7	3.5	3.9	1.3
15:00	306	3.4	3.4	3.6	1.4
16:00	400	4.5	4.7	3.6	1.7
17:00	295	3.3	3.2	3.2	1.3
18:00	185	2.1	2.0	2.1	0.8
19:00	169	1.9	1.7	3.0	0.8
20:00	178	2.0	1.7	3.0	0.8
21:00	243	2.7	2.3	5.5	1.2
22:00	217	2.4	2.2	4.6	1.1
23:00	240	2.7	2.5	6.2	1.4

“Articles”: number of time-stamped articles published in each hour (New York time).
“Pooled”: share of all time-stamped articles. “Trading days” and “Closed days”: mean over days of the daily hourly shares. “Placebo”: mean daily shares when articles without a time and articles stamped 00:00 are placed at 00:00.

Table B.4: Availability of publication times by newspaper

Newspaper	Articles	Timed (%)	No time (%)	00:00 (%)
Dow Jones Institutional News	1,588	99.8	0.0	0.2
Dow Jones Newswires	1,131	99.7	0.0	0.3
Agence France Presse	764	100.0	0.0	0.0
Financial Times (FT.Com)	701	82.3	0.0	17.7
Financial Times	615	0.0	100.0	0.0
The Times of India	569	0.0	100.0	0.0
Mint	469	0.0	100.0	0.0
The Economic Times	460	0.0	100.0	0.0
South China Morning Post	449	0.0	100.0	0.0
scmp.com	423	0.0	100.0	0.0
The Guardian	404	99.5	0.0	0.5
The Wall Street Journal Online	396	98.5	1.0	0.5
The Globe and Mail (Breaking News)	379	0.0	100.0	0.0
The Canadian Press	311	91.6	0.0	8.4
The New York Times	308	0.0	100.0	0.0
Mail Online	298	100.0	0.0	0.0
The Toronto Star	296	0.0	100.0	0.0
The Globe and Mail	291	0.0	100.0	0.0
World Service Wire	281	100.0	0.0	0.0
China Daily	260	0.0	100.0	0.0

The 20 newspapers with the most articles in the sample.

Table B.5: NYSE holidays in the sample

Date	Weekday	Holiday	Articles	Timed
2025-04-18	Friday	Good Friday	197	70
2025-05-26	Monday	Memorial Day	104	38
2025-06-19	Thursday	Juneteenth	72	30
2025-07-04	Friday	Independence Day	84	39

Weekdays on which the NYSE was closed. “Timed”: articles with a time stamp.

C Narrative Characterizations

C.1 Characterizations

Narrative 1. Global Market Meltdown and Escalating US-China Tariff War

Community id 0; size 2,169 stories.

Metric	Value
Nodes	2,169
Edges	1,093,151
Density	0.4649
Average degree	1,007.98
Average similarity	2.5364
Min similarity	1.2800
Max similarity	28.297
Clustering coefficient	0.7146

Characterization. This community focuses on the immediate financial market chaos following Trump's April 2025 "Liberation Day" tariff announcements, particularly the catastrophic stock market crashes across Asia and Europe. It distinctively emphasizes the rapid escalation between the US and China to triple-digit tariff rates (145% US, 125% China) and the subsequent market panic, with specific attention to historic single-day losses and Trump's dismissal of investor concerns as necessary "medicine."

Key events.

- On April 2, 2025, US President Donald Trump announced sweeping new tariffs including a baseline 10% levy on almost all imports and custom 'reciprocal' tariffs on countries he considers to have pursued unfair trade policies, with 20% tariffs against the EU and 34% on Chinese products.
- On Monday, April 7, 2025, Hong Kong's stock exchange closed with a 13.22% drop (its worst one-day tumble since the 1997 Asian financial crisis), Taiwan's Taiex plunging 9.8%, Shanghai Composite losing 4.4%, Singapore's Straits Times Index plunging 7.37%, and India's Nifty index falling more than 3.5%.
- On Monday, April 7, 2025, European stock markets followed Asian markets into

freefall, with Germany's DAX index dropping nearly 10% at opening before recovering slightly to around 7% losses.

- On Friday (before April 6), China retaliated by imposing its own 34% tariff against US goods, matching Trump's reciprocal tariffs, with implementation starting April 10.
- On Tuesday (April 22, 2025), Trump said he was willing to 'substantially' pare back tariffs on China and would announce actual tariffs over the next two to three weeks, reversing his aggressive stance because of market reactions and adviser counsel.

Key predictions.

- JPMorgan economists predict a 60% chance that the world will tip into a recession this year in light of Trump's tariffs.
- Most economists predict that the tariffs will have a negative impact on the US economy, sending up prices and unemployment and likely triggering a recession.
- Goldman Sachs predicts a 45% probability of a US recession in the next year.
- Capital Economics predicts US inflation could rise above 5% and a worsening recession if Congress fails to pass timely fiscal stimulus.
- The damage done to the US and global economies and America's relationships with the rest of the world is likely to be long-lasting, if not permanent, because Trump has torn up the world order and demonstrated his isolationist, transactional agenda.

Representative stories.

- story_7526 [central]: High eigenvector centrality (1.000)

Source article: Trump tariffs: EU ministers to meet as global markets tumble (2025-04-06)

Events:

1. On April 2, 2025, US President Donald Trump announced sweeping new tariffs including a baseline 10% levy on almost all imports and custom 'reciprocal' tariffs on countries he considers to have pursued unfair trade policies, with 20% tariffs against the EU and 34% on Chinese products.
2. Before Trump's tariff announcement last week, European Commission President Ursula von der Leyen offered the United States 'zero-for-zero' tariffs on flows of industrial goods to avert a transatlantic trade war.
3. On Saturday, April 5, 2025, Trump's baseline 10% tariffs came into effect on almost all imports into the US.
4. On Friday (before April 6), China retaliated by imposing its own 34% tariff against US goods, matching Trump's reciprocal tariffs, with implementation starting April 10.
5. On Sunday, April 6, 2025, US Treasury Secretary Scott Bessent said that more than 50 countries had started talks with the Trump administration about the tariffs.

6. On Sunday, April 6, 2025, Trump told reporters that investors must endure the consequences, calling the market turmoil necessary 'medicine' and saying he wasn't concerned about massive sell-offs.
7. On Monday, April 7, 2025, Asian stock markets experienced massive losses, with Hong Kong's stock exchange closing with a 13.22% drop (its worst one-day tumble since the 1997 Asian financial crisis), Taiwan's Taiex plunging 9.8%, Shanghai Composite losing 4.4%, Singapore's Straits Times Index plunging 7.37%, and India's Nifty index falling more than 3.5%.
8. On Monday, April 7, 2025, European stock markets followed Asian markets into freefall, with Germany's DAX index dropping nearly 10% at opening before recovering slightly to around 7% losses, Paris dropping more than 6%, London falling just under 6%, Amsterdam and Oslo losing more than 5%, and Milan losing over 3%.
9. On Monday, April 7, 2025, EU trade ministers met in Luxembourg to discuss a unified response to Trump's tariffs and assess strategies to convince Trump to rethink his trade moves.
10. On Monday, April 7, 2025, JPMorgan CEO Jamie Dimon warned in his annual letter to shareholders that Trump's tariffs will likely have an inflationary impact in the US and could trigger a recession, with JPMorgan economists giving a 60% chance the world will tip into recession this year.
11. On Monday, April 7, 2025, Trump posted on Truth Social trying to play up tariff achievements while attacking China for imposing retaliatory tariffs, calling for the Fed to cut interest rates, and making no mention of trillions of dollars wiped off global stock markets.

Predictions:

1. Trump's custom reciprocal tariffs (including 20% on EU goods and 34% on Chinese products) will come into effect on Wednesday, April 9, 2025.
2. The EU will target US goods from mid-April with retaliatory tariffs including Harley Davidson motorbikes and agricultural products from politically important US states.
3. JPMorgan economists predict a 60% chance that the world will tip into a recession this year in light of Trump's tariffs.
4. Most economists predict that the tariffs will have a negative impact on the US economy, sending up prices and unemployment and likely triggering a recession.
5. The situation for global markets will likely get worse according to Germany's likely next chancellor Friedrich Merz.

• story_16948 [central]: High eigenvector centrality (0.963)

Source article: The Trump administration is just making it up as it goes (2025-04-23)

Events:

1. On April 2, 2025, Donald Trump announced a 10 percent universal baseline tariff and punitive reciprocal tariffs on about 90 countries during 'Liberation Day' to implement his trade policy.
2. China imposed 125 percent retaliatory tariffs in response to Trump's 145 percent tariff on Chinese imports because Trump initiated the trade war with aggressive tariffs.
3. One week before April 23, 2025, Trump criticized Federal Reserve Chair Jerome Powell for saying tariffs would impact inflation and for keeping interest rates on hold, threatening Powell's termination because Trump disagreed with Powell's assessment.
4. On Monday (April 21, 2025), executives from Walmart, Home Depot, and Target met with Trump and warned him of disrupted supply chains, higher prices, and empty shelves to convince him to reconsider his tariff policies.
5. On Tuesday (April 22, 2025), Treasury Secretary Scott Bessent told investors in a closed-door meeting that the US and China would have to de-escalate tariffs in the 'very near future' because the 145 percent and 125 percent tariffs couldn't be sustained.
6. On Tuesday (April 22, 2025), Trump said he was willing to 'substantially' pare back tariffs on China and would announce actual tariffs over the next two to three weeks, reversing his aggressive stance because of market reactions and adviser counsel.
7. On Tuesday (April 22, 2025), Trump said he had no intention of firing Jerome Powell, reversing his earlier threats because Bessent

and Lutnick warned that Powell's removal would ignite chaos in financial markets.

8. After meetings with Apple and other tech companies, Trump announced exemptions for imports of computers and electronic products to reduce the impact on the technology sector.
9. Financial markets reacted violently throughout April 2025 by plunging in response to tariff announcements and rebounding when Trump indicated tariffs might be eased because investors lost faith in America's economic stability.

Predictions:

1. Trump will have to make an opening, conciliatory move toward China to end the trade embargo and prevent decoupling of the world's two biggest economies.
2. The tariffs will lead to higher prices for US consumers, lower profit margins for big US

companies, insolvency for many smaller US businesses, lower US economic growth with higher inflation, and political pain for Trump and Congressional Republicans if China does nothing.

3. It could take several years to finalize the terms of trade deals with the 90-odd countries affected by reciprocal tariffs, despite the 90-day negotiation period Trump announced.
4. The turbulence in markets is unlikely to be over, and the damage to the US reputation and economy has not been contained because of Trump's propensity to shoot from the lip and his infatuation with tariffs.
5. The damage done to the US and global economies and America's relationships with the rest of the world is likely to be long-lasting, if not permanent, because Trump has torn up the world order and demonstrated his isolationist, transactional agenda.

• story_7500 [central]: High eigenvector centrality (0.958)

Source article: Global stocks plummet as Trump tariffs stoke recession fears (2025-04-07)

Events:

1. US President Donald Trump announced unprecedented tariffs on most US trading partners on Wednesday, April 2, 2025, to correct trade imbalances between the US and its major trading partners.
2. China ordered retaliatory tariffs of 34% on American goods and imposed export curbs on rare earths following Trump's tariff announcement on Wednesday, April 2, 2025, with these measures due to take effect on Thursday, April 10, 2025.
3. Global stock markets plunged for three consecutive days from Friday, April 4 through Monday, April 7, 2025, as investors reacted to Trump's tariffs by selling off stocks due to fears of a global recession.
4. Trump told reporters aboard Air Force One on Sunday evening, April 6, 2025, that investors would have to deal with the market sell-off, saying 'Sometimes you have to take medicine to fix something,' which exacerbated further stock declines.
5. More than 50 countries contacted Washington on Sunday, April 6, 2025, to seek new trade deals in response to Trump's tariffs.
6. EU finance ministers met in Luxembourg on Monday, April 7, 2025, and agreed on ap-

proximately 26 billion of new levies in response to Trump's earlier 25% tariffs on aluminum and steel.

7. Trump threatened China with an additional 50% tariff on Monday, April 7, 2025, if Beijing doesn't withdraw its latest 34% tariff increase.

Predictions:

1. JP Morgan predicts a 60% probability of a global recession by the end of 2025.
2. S&P Global predicts a 30-35% probability of a US recession.
3. Goldman Sachs predicts a 45% probability of a US recession in the next year.
4. Capital Economics predicts US inflation could rise above 5% and a worsening recession if Congress fails to pass timely fiscal stimulus.
5. Goldman Sachs predicts the new tariffs will lower Chinese GDP growth by at least 0.7 percentage points in 2025.
6. Kaiyuan Securities predicts the tariffs could slash Chinese exports to the US by almost a third, cut overall exports by more than 4.5%, and drag economic growth by 1.3 percentage points.
7. Paul Ashworth from Capital Economics pre-

dicts Trump will quickly announce deals that reduce prohibitive reciprocal tariff rates on

some of the hardest hit countries, with China possibly being the exception.

- story_1688 [central]: High eigenvector centrality (0.940)

Source article: Trump doubles down on tariffs despite warnings on Wall Street (2025-04-08)

Events:

1. President Trump announced sweeping tariffs on trading partners last week (before April 8, 2025), imposing a baseline 10-percent duty on imports with higher rates for dozens of countries to push the United States' average tariff rate to the highest level in a century.
2. Major U.S. stock indexes lost more than 10 percent on Thursday and Friday (April 3-4, 2025) in the United States as investors responded with panic to Trump's tariff announcement.
3. China announced 34-percent retaliatory tariffs against U.S. goods on Friday (April 4, 2025) in Beijing in response to Trump's tariffs.
4. The baseline tariff came into force over the weekend (April 5-6, 2025) in the United States as Trump proceeded with his tariff plan.
5. Larry Fink, CEO of BlackRock, said the U.S. economy was weakening and many executives would say the country is probably in a recession on Monday (April 7, 2025) at the Economic Club of New York because the market rout could have a real impact on the economy.
6. Jamie Dimon, CEO of JPMorgan Chase, warned that the recent tariffs will likely increase inflation and are causing many to consider a greater probability of a recession on Monday (April 7, 2025) in his annual letter to shareholders published that day because of the economic impact of the tariffs.
7. The S&P 500 opened down around 4 percent on Monday morning (April 7, 2025), then jumped 8 percent after a false report that Trump was pausing tariffs for 90 days, then sold off after the White House denied the report in the United States as markets fluctuated wildly.
8. Trump doubled down on his support for tariffs and threatened an additional 50-percent levy on China on Monday (April 7, 2025) at an Oval Office press conference in response to China's 34-percent retaliatory tariffs because he had no intention of pausing the tariffs.
9. Canada imposed 25-percent retaliatory tariffs on U.S. automobiles and around \$60-billion of other U.S. goods by Monday (April 7, 2025) in Canada in response to U.S. tariffs on Canadian goods.
10. The European Union offered to cut tariffs to zero on American-made cars and other industrial products by Monday (April 7, 2025) in Europe to negotiate with the Trump administration and avoid retaliation.
11. U.S. Treasury Secretary Scott Bessent said more than 50 countries had reached out to the administration in recent days on Monday (April 7, 2025) via social-media post because countries wanted to negotiate deals with the United States.

Predictions:

1. The country-specific tariffs will begin on Wednesday (April 9, 2025) in the United States as Trump proceeds with his tariff plan by implementing the higher country-specific tariff rates.
2. Larry Fink predicts the turmoil is going to freeze more and more consumption and the U.S. will start seeing that really quickly in the United States because the market impact is impacting Main Street through declining equity values.
3. Bill Ackman predicts that if the U.S. proceeds as planned with tariffs, business investment will grind to a halt, consumers will close their wallets and pocketbooks, and the U.S. will severely damage its reputation with the rest of the world that will take years and potentially decades to rehabilitate in the United States because of the economic nuclear war created by the tariffs.

- story_7816 [central]: High eigenvector centrality (0.929)

Source article: Donald Trump's sweeping tariffs ignite \$2.5tn rout on Wall Street (2025-04-04)

Events:

1. On Wednesday, April 2, 2025, Donald Trump announced a universal levy of 10 percent on nearly all US imports effective April 5 and reciprocal tariffs as high as 50 percent on dozens of countries effective April 9, with levies on Chinese exports potentially rising to more than 60 percent.
 2. On Thursday, April 3, 2025, the S&P 500 tumbled 4.8 percent and the Nasdaq Composite plunged 6 percent, wiping out about \$2.5 trillion in market value from Wall Street equities as investors reacted to Trump's tariff announcement.
 3. On Thursday, April 3, 2025, Apple's shares slid 9.3 percent, wiping more than \$300 billion off the company's market capitalization in its worst market cap fall on record as investors braced for the impact on its Asian manufacturing hubs.
 4. On Thursday, April 3, 2025, China's commerce ministry stated that Beijing would resolutely take countermeasures to protect its own rights and interests in response to Trump's tariffs.
 5. On Thursday, April 3, 2025, Stellantis announced it would furlough 900 workers at five US plants due to a temporary shutdown of production in Canada and Mexico in response to Trump's 25 percent tariffs on foreign car imports.
 6. On Thursday evening, April 3, 2025, Donald Trump defended his tariff plans, stating he had expected market ructions and that the tariffs would usher in a booming economy.
 7. On Thursday, April 3, 2025, French President Emmanuel Macron urged European companies to pause investment in the US and stated that nothing is excluded in terms of retaliation.
 8. On Friday, April 4, 2025, European stocks extended their declines with the Stoxx Europe 600 falling 1 percent, Japan's Topix closing 3.4 percent lower, and the dollar falling a further 0.2 percent, wiping out its gains since Trump's election victory.
- Predictions:*
1. Analysts predict that Trump's tariff measures could sharply reduce China's GDP growth this year and push China to shift from manufacturing for export towards domestic consumption.
 2. Economists predict that the new tariff duties would stoke inflation and hit growth in the US.
 3. IMF managing director Kristalina Georgieva warns that the Trump administration's new tariffs represent a significant risk to the global economic outlook at a time of sluggish growth.
 4. Investors are betting on more rate cuts from the Federal Reserve based on movements in shorter-dated Treasury bonds.
- story_16948 [coverage] (centrality 0.9626): Covers 88.7% of community (1923/2169 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 2. Chronological Tariff Implementation and Retaliatory Measures Timeline

Community id 1; size 1,904 stories.

Metric	Value
Nodes	1,904
Edges	1,151,392
Density	0.6355
Average degree	1,209.45
Average similarity	2.8173
Min similarity	1.2800
Max similarity	36.361
Clustering coefficient	0.8158

Characterization. This community provides a comprehensive chronological account of tariff implementations and retaliations from February through July 2025, tracking the step-by-step escalation and occasional pauses. It distinctively documents the specific dates when tariffs took effect, were paused, or were modified, including the 90-day negotiation windows and subsequent extensions, creating a detailed procedural timeline of the trade war’s evolution.

Key events.

- On February 1st, 2025, the US announced steep new tariffs on Canada, Mexico and China to alter trade relationships with these countries.
- On February 3rd, 2025, the US placed the Mexico and Canada tariffs on hold for 30 days to allow for negotiations.
- On March 4th, 2025, the US implemented delayed 25 percent tariffs on Mexico and Canada and announced an additional 10 percent levy on Chinese imports to increase trade pressure, and Canada announced a retaliatory package in response.
- On April 9th, 2025, Trump announced an increase of the US tariff rate on China to as high as 145 percent and a 90-day pause on tariffs for other countries to intensify pressure on China while providing relief to other nations.
- On May 12th, 2025, China and the US agreed to lower tariffs for the next 90 days to de-escalate the trade war.

Key predictions.

- Trump will have to make an opening, conciliatory move toward China to end the trade embargo and prevent decoupling of the world’s two biggest economies.

- It could take several years to finalize the terms of trade deals with the 90-odd countries affected by reciprocal tariffs, despite the 90-day negotiation period Trump announced.
- The tariffs will lead to higher prices for US consumers, lower profit margins for big US companies, insolvency for many smaller US businesses, lower US economic growth with higher inflation, and political pain for Trump and Congressional Republicans if China does nothing.
- The turbulence in markets is unlikely to be over, and the damage to the US reputation and economy has not been contained because of Trump's propensity to shoot from the hip and his infatuation with tariffs.

Representative stories.

- story_2511 [central]: High eigenvector centrality (1.000)

Source article: The tariffs timeline (2025-07-15)

Events:

1. On February 1st, 2025, the US announced steep new tariffs on Canada, Mexico and China to alter trade relationships with these countries.
2. On February 3rd, 2025, the US placed the Mexico and Canada tariffs on hold for 30 days to allow for negotiations.
3. On February 4th, 2025, the US implemented tariffs on China and Beijing revealed a retaliatory package in response to the US tariffs.
4. On March 4th, 2025, the US implemented delayed 25 percent tariffs on Mexico and Canada and announced an additional 10 percent levy on Chinese imports to increase trade pressure, and Canada announced a retaliatory package in response.
5. On March 6th, 2025, the US issued new executive orders that backtracked on sweeping 25 percent tariffs on Mexico and Canada to adjust trade policy.
6. On March 11th, 2025, the US announced an additional 25 percent tariff on steel and aluminium imports from Canada to protect domestic industries, and Canada retaliated with new tariffs on almost \$21 billion of US goods.
7. On March 26th, 2025, Donald Trump announced the US will impose tariffs of 25 percent on foreign-made car imports to protect the domestic auto industry, and other nations planned reprisals in response.
8. On April 2nd, 2025, Trump announced the US will impose tariffs ranging from 10 to 50 percent on 185 countries, with a universal 10 percent tariff starting April 5th and other tariffs beginning April 9th, to reshape global trade relationships.
9. On April 4th, 2025, China unveiled 34 percent retaliatory tariffs in response to US tariff announcements.
10. On April 9th, 2025, the US proceeded with another 50 percent tariff on Chinese goods and China announced an additional retaliatory tariff of 50 percent on US imports in response to escalating trade tensions.
11. On April 9th, 2025, Trump announced an increase of the US tariff rate on China to as high as 145 percent and a 90-day pause on tariffs for other countries to intensify pressure on China while providing relief to other nations.
12. On April 11th, 2025, China increased retaliatory tariffs on US imports to 125 percent in response to the US tariff increase to 145 percent, and the US announced it will exempt smartphones and other consumer electronics from its steep reciprocal tariffs, though Trump later signaled this reprieve is temporary.
13. On April 29th, 2025, Trump issued an executive order offering car manufacturers some relief from tariffs to ease pressure on the auto

industry.

14. On May 8th, 2025, the US and Britain reached the first deal of the trade war with cuts to punitive tariffs on British car and steel exports but kept 10 percent US levies on other exports to begin resolving trade disputes.
15. On May 12th, 2025, China and the US agreed to lower tariffs for the next 90 days to de-escalate the trade war.
16. On May 25th, 2025, Trump agreed to delay a threatened 50 percent tariff on the European Union and extend trade negotiations until July 9th after a conversation with European Commission president Ursula von der Leyen to allow more time for negotiations.
17. On May 28th, 2025, a US trade court ruled that Trump's global tariffs are illegal because they violated trade law.
18. On May 30th, 2025, Trump announced he will double steel and aluminium tariffs to 50 percent with the new levies set to take effect from June 4th in response to the court ruling or to increase pressure.
19. On July 10th, 2025, Trump set a tariff on copper of 50 percent effective August 1st and threatened a 200 per cent levy on pharmaceuticals to expand tariff coverage to additional sectors.
20. On July 12th, 2025, Trump announced a 30 percent tariff on Mexico and the EU for August 1st to continue applying trade pressure.

- story_20679 [central]: High eigenvector centrality (0.987)

Source article: The tariffs timeline (2025-07-15)

Events:

1. On February 1st, 2025, the US announced steep new tariffs on Canada, Mexico and China to protect domestic industries.
2. On February 3rd, 2025, the US placed tariffs on Mexico and Canada on hold for 30 days to allow for negotiations.
3. On February 4th, 2025, the US implemented tariffs on China, and Beijing revealed a retaliatory package in response to the US tariffs.
4. On February 10th, 2025, the US set 25 per cent tariffs on aluminium and steel imports to protect domestic metal industries, expected to take effect March 12th.
5. On March 4th, 2025, the US implemented delayed 25 per cent tariffs on Mexico and Canada after the 30-day hold expired, announced an additional 10 per cent levy on Chinese imports to increase pressure, and Canada announced a retaliatory package in response to US tariffs.
6. On March 6th, 2025, the US issued new executive orders that backtracked on sweeping 25 per cent tariffs on Mexico and Canada due to NA.
7. On March 11th, 2025, the US announced an additional 25 per cent tariff on steel and aluminium imports from Canada to protect domestic industries, and Canada retaliated with new tariffs on almost \$21 billion of US goods in response to US tariffs.
8. On March 24th, 2025, the US announced tariffs against countries that buy Venezuelan oil to pressure Venezuela economically.
9. On March 26th, 2025, Donald Trump announced the US will impose tariffs of 25 per cent on foreign-made car imports to protect domestic auto manufacturing, and other nations planned reprisals in response to the car tariffs.
10. On April 2nd, 2025, Trump announced the US will impose tariffs ranging from 10 to 50 per cent on 185 countries, with a universal 10 per cent tariff on all countries starting April 5th and other tariffs beginning April 9th, to address trade imbalances.
11. On April 4th, 2025, China unveiled 34 per cent retaliatory tariffs in response to US tariffs announced on April 2nd.
12. On April 8th, 2025, the White House confirmed plans to proceed with another 50 per cent tariff on Chinese goods effective April 9th to escalate trade pressure on China.
13. On April 9th, 2025, China announced an additional retaliatory tariff of 50 per cent on US imports in response to the 50 per cent US tariff, and Trump announced an increase of the US tariff rate on China to as high as 145 per cent in response to China's retaliation and announced a 90-day pause on tariffs for other countries to allow for negotiations.
14. On April 11th, 2025, China increased retaliatory tariffs on US imports to 125 per cent in response to Trump's 145 per cent tariff increase, and the US announced it will exempt

smartphones and other consumer electronics from its steep reciprocal tariffs to protect consumers, but Trump later signaled this reprieve is temporary.

15. On April 29th, 2025, Trump issued an executive order offering car manufacturers some relief from tariffs through NA.
16. On May 8th, 2025, the US and Britain reached the first deal of the trade war that saw cuts to punitive tariffs on British car and steel exports but kept 10 per cent US levies on other exports through negotiations.
17. On May 12th, 2025, China and the US agreed to lower tariffs for the next 90 days through negotiations to de-escalate the trade war.
18. On May 25th, 2025, Trump agreed to delay a threatened 50 per cent tariff on the European Union and extend trade negotiations

until July 9th after a conversation with European Commission president Ursula von der Leyen.

19. On May 28th, 2025, a US trade court ruled that Trump's global tariffs are illegal through judicial review.
20. On May 30th, 2025, Trump said he will double steel and aluminium tariffs to 50 per cent with the new levies set to take effect from June 4th in response to NA.
21. On July 10th, 2025, Trump set a tariff on copper of 50 per cent effective August 1st to NA and threatened a 200 per cent levy on pharmaceuticals to NA.
22. On July 12th, 2025, Trump announced a 30 per cent tariff on Mexico and the EU for August 1st to NA.

- story_18410 [central]: High eigenvector centrality (0.985)

Source article: Trump tariffs on China now stands at 145%, White House confirms (2025-04-10)

Events:

1. In February 2025, Donald Trump imposed a 10% tariff on all Chinese goods citing Beijing's alleged role in fueling illegal immigration and facilitating fentanyl flow into the United States.
2. Last month (March 2025), Donald Trump doubled the tariff rates from February, sending shockwaves through global markets and deepening US-China relations.
3. Donald Trump initially imposed a 34% tariff on Chinese goods, and Beijing swiftly imposed an equivalent retaliatory measure in response.
4. The US added another 50% in duties in response to China's retaliatory tariff.
5. On Tuesday (April 8, 2025), Donald Trump announced a 104% tariff on all Chinese imports, bringing the US and China dangerously close to a full-blown trade war.
6. On Wednesday (April 9, 2025), Donald Trump reversed his sweeping tariffs on most nations for at least 90 days but ramped up pressure on China by raising tariffs to 125% from 84% and adding a 20% fentanyl-related

tariff.

7. On Thursday (April 10, 2025), the White House confirmed that total US tariffs on Chinese imports now stand at 145%.
8. On Thursday (April 10, 2025) at 12:01 pm, China's 84% tariffs on US imports came into effect.
9. On Thursday (April 10, 2025), a Chinese Ministry of Commerce spokesperson stated that Beijing remains open to dialogue but will only negotiate on the basis of mutual respect and equality.
10. On Thursday (April 10, 2025), China's foreign ministry accused the US of bullying and warned that Trump's approach would end in failure.

Predictions:

1. The trade confrontation between the US and China threatens to hit domestic industries hard with businesses experiencing cost surges, layoffs, and reduced competitiveness.
2. Analysts raise the specter of an American recession due to the trade war between the world's two largest economies.

- story_18643 [central]: High eigenvector centrality (0.964)

Source article: China hits back at US, raises tariffs to 84% starting April 10 (2025-04-09)

Events:

1. In February 2025, President Donald Trump imposed a 10 percent tariff on all Chinese goods in the United States, citing Beijing's alleged role in fueling illegal immigration and facilitating the flow of fentanyl into the United States.
2. Last month (March 2025), President Donald Trump doubled the tariff rates on Chinese goods in the United States, sending shockwaves through global markets and deepening already strained US-China relations.
3. President Donald Trump initially imposed a 34 percent tariff on Chinese goods in the United States as part of escalating trade measures.
4. Beijing swiftly imposed an equivalent 34 percent retaliatory tariff on US goods in China in response to Trump's 34 percent tariff.
5. The US added another 50 percent in duties on Chinese imports in the United States, bringing the total tariff burden to 104 percent when combined with earlier levies.
6. President Donald Trump announced a staggering 104 percent tariff on all Chinese imports in the United States on Tuesday (April 8, 2025), with the tariff set to take effect on April 9, 2025.
7. The 104 percent US tariff on Chinese goods officially came into effect just after midnight Wednesday (April 9, 2025) US time.
8. China sharply criticized the United States at the World Trade Organization on April 9, 2025, warning that Trump's sweeping reciprocal tariffs threaten to further destabilize global trade and violate WTO rules.
9. Chinese Foreign Ministry spokesperson Lin Jian condemned Washington's tariff moves at a daily press briefing on April 9, 2025, stating China will take firm and resolute measures to safeguard legitimate rights and interests.
10. China's finance ministry announced on Wednesday (April 9, 2025) that China will raise tariffs on a wide range of US goods to 84 percent starting Thursday (April 10, 2025), escalating from the previously announced 34 percent.

Predictions:

1. The extreme tariffs could trigger an unmanaged decoupling of trade between the US and China, risking reignited volatility in global markets in the immediate term.
2. The rising tariffs threaten to hit domestic industries hard, with businesses warning of cost surges, layoffs, and reduced competitiveness.

• story_18645 [central]: High eigenvector centrality (0.947)

Source article: Firmly oppose bullying: China releases white paper as trade war with US escalates (2025-04-09)

Events:

1. In 1979, China and the US had bilateral trade volume of less than \$2.5 billion, which grew to nearly \$688.3 billion by 2024 with two-way investment exceeding \$260 billion.
2. During Trump's first term, the US imposed tariffs on Chinese goods, bringing the average US tariff on Chinese goods to 19.3 percent by the end of his first term.
3. The Biden administration maintained and expanded Trump's tariffs, bringing the average tariff rate to 20.8 percent.
4. In February 2025, Donald Trump slapped a 10 percent tariff on all Chinese goods, citing Beijing's alleged role in fueling illegal immigration and facilitating the flow of fentanyl into the United States.
5. Last month (March 2025), Trump doubled the tariff rates from February, sending shockwaves through global markets and deepening US-China relations.
6. Trump initially planned to impose a 34 percent tariff hike on China under his 'reciprocal' tariff plan.
7. Beijing vowed to slap 34 percent retaliatory tariffs on US goods by Tuesday noon (April 8, 2025).
8. After China refused to reverse its retaliatory tariff vow, Trump added another 50 percent in penalties, bringing the total to an additional 84 percent on top of existing tariffs.
9. On Tuesday (April 8, 2025), China's Commerce Ministry said it 'firmly opposes' the additional 50% tariffs on Chinese imports and vowed to escalate its retaliation on US exports.
10. White House Press Secretary Karoline Leavitt

confirmed on Tuesday (April 8, 2025) that the US would impose a 104% tariff on all Chinese imports starting Wednesday (April 9, 2025).

11. On April 9, 2025, China issued a white paper titled 'China's Position on Several Issues in China-US Economic and Trade Relations' in response to Trump's 104 percent tariff, warning of retaliation and accusing the US of economic bullying and unilateralism.
12. Chinese foreign ministry spokesperson Lin Jian spoke to reporters at a regular media briefing, saying the US continued to impose

tariffs on China indiscriminately.

Predictions:

1. The total average tariff rate on Chinese exports to the US will surge to nearly 125 percent once the latest duties are fully implemented on Wednesday.
2. The rising tariffs will hit domestic industries hard, with businesses experiencing cost surges, layoffs, and reduced competitiveness.
3. Beijing will take decisive action to defend its interests if provoked further.

- story_13008 [coverage] (centrality 0.8409): Covers 92.8% of community (1767/1904 nodes)

Source article: Trump's tariff blitz could hardly have come at a worse time for China (2025-04-12)

Events:

1. President Trump imposed 145 percent tariffs on all Chinese goods in early April 2025, effectively launching a trade embargo on China during a period when China's economy was struggling with property market slump, high youth unemployment, and weak domestic spending threatening deflation.
2. Within less than a week in early April 2025, the United States and China progressively escalated tariffs to historic highs, with the U.S. imposing 145 percent tariffs on Chinese goods and China imposing at least 125 percent tariffs on American shipments.
3. On Wednesday April 9, 2025, Trump granted other countries a 90-day reprieve from some Liberation Day tariffs but simultaneously hit China with an additional levy effective immediately.
4. On Friday April 11, 2025, China responded by announcing additional retaliatory tariffs to take effect Saturday April 12, 2025, stating it was ready to fight to the end.
5. On Thursday April 10, 2025, Goldman Sachs lowered its forecast for China's GDP growth from around 5 percent to 4 percent due to the tariffs.
6. On Thursday April 10, 2025, Chinese economic data showed consumer prices continued to slide in March, indicating persistent

deflation as consumers held back spending.

7. In the three days following the tariff announcement in early April 2025, Aron Gu, owner of a shoe-material factory in Guangdong province, lost 80 percent of his orders and put most of his 100-plus employees on unpaid leave.
8. On Thursday and Friday April 10-11, 2025, China's stock shares closed higher after Trump's partial rollback of tariffs lowered the risk of U.S. or global recession.

Predictions:

1. China will likely implement stimulus measures including child care subsidies, pension support, and expanded trade-in schemes as soon as the end of April 2025 at a high-level meeting of senior leaders.
2. China may cut interest rates or reduce commercial bank reserve requirements to encourage more lending to Chinese companies.
3. An avalanche of Chinese goods will have to find new markets in Europe or the Global South, potentially causing a tsunami of exports that could trigger trade barriers in those regions.
4. Trump could expand U.S. export controls on advanced semiconductors, machine tools, and biotechnology equipment, which would be more disruptive for China's development in the short run than trade tariffs.

Narrative 3. Economic Forecasts and Growth Downgrades from International Organizations

Community id 2; size 1,453 stories.

Metric	Value
Nodes	1,453
Edges	249,896
Density	0.2369
Average degree	343.97
Average similarity	2.6001
Min similarity	1.2800
Max similarity	30.171
Clustering coefficient	0.5638

Characterization. This community centers on official economic projections and forecast revisions by major institutions like the OECD, focusing on how tariffs forced dramatic downgrades to GDP growth expectations for 2025-2026. It distinctively emphasizes quantitative economic modeling and institutional analysis, particularly the OECD's June 2025 forecast slashing US growth from 2.2% to 1.6% and global growth to 2.9%, with specific attention to inflation acceleration and interest rate implications.

Key events.

- President Trump imposed a tariff regime that brought the average effective tariff rate to above 15% (the highest since World War II) from about 2.5% previously, with tariffs in place as of mid-May assumed to remain through 2026.
- The U.S. GDP contracted at a 0.2% annual rate in the first quarter of 2025 as businesses ramped up imports ahead of the Trump tariffs.
- The OECD released a new forecast on June 4, 2025, sharply cutting its U.S. economic outlook, expecting GDP growth to decelerate to 1.6% in 2025 from 2.8% in 2024 (down from its previous 2.2% forecast) due to tariff effects, retaliation from other countries, economic policy uncertainty, and slower immigration.
- A U.S. federal trade court ruled last week (late May 2025) that Trump didn't have the authority to impose sweeping tariffs on virtually every nation, but a federal appeals court temporarily put that ruling on hold.

- Export Development Canada released a report on July 16, 2025 forecasting Canada will fall into recession during 2025.

Key predictions.

- U.S. GDP growth will decelerate to 1.6% in 2025 from 2.8% in 2024.
- U.S. inflation, as measured by the personal-consumption expenditures price index, will pick up to 3.9% by the end of 2025.
- The Federal Reserve will keep interest rates steady through 2025 and will not cut rates again until 2026.
- Global economic growth will be 2.9% in both 2025 and 2026, down from 3.3% in 2024.
- Canada will experience a recession during 2025 with two consecutive quarters of declining GDP.

Representative stories.

- story_10204 [central]: High eigenvector centrality (1.000)

Source article: Tariffs Are Projected to Slow U.S. Growth, Raise Inflation — OECD cuts outlook, expects the Federal Reserve to keep rates steady this year (2025-06-04)

Events:

1. President Trump imposed a tariff regime that brought the average effective tariff rate to above 15% (the highest since World War II) from about 2.5% previously, with tariffs in place as of mid-May assumed to remain through 2026.
2. The U.S. GDP contracted at a 0.2% annual rate in the first quarter of 2025 as businesses ramped up imports ahead of the Trump tariffs.
3. In May 2025, Trump announced the U.S. would hold off implementing a threatened 50% tariff on goods from the European Union until July 9.
4. A U.S. federal trade court ruled last week (late May 2025) that Trump didn't have the authority to impose sweeping tariffs on virtually every nation, but a federal appeals court temporarily put that ruling on hold.
5. On Tuesday (June 3, 2025), Trump signed an executive order doubling tariffs on im-

ported steel and aluminum effective Wednesday, aiming to boost the domestic industry and protect U.S. jobs.

6. The OECD released a new forecast on June 4, 2025, sharply cutting its U.S. economic outlook, expecting GDP growth to decelerate to 1.6% in 2025 from 2.8% in 2024 (down from its previous 2.2% forecast) due to tariff effects, retaliation from other countries, economic policy uncertainty, and slower immigration.

Predictions:

1. U.S. GDP growth will decelerate to 1.6% in 2025 from 2.8% in 2024.
2. U.S. inflation, as measured by the personal-consumption expenditures price index, will pick up to 3.9% by the end of 2025.
3. The Federal Reserve will keep interest rates steady through 2025 and will not cut rates again until 2026.
4. Imports will slow sharply in the second quarter of 2025, with the Atlanta Fed's GDPNow

model predicting growth of 4.6% in the second quarter.

5. Global economic growth will be 2.9% in both 2025 and 2026, down from 3.3% in 2024.
6. Mexico's economy will grow just 0.4% in 2025.

7. Canada's economy will expand by 1% in 2025.

8. The European Central Bank will continue its recent cuts to its policy rate at a meeting this week (early June 2025).

- story_20651 [central]: High eigenvector centrality (0.994)

Source article: Canada Likely to Fall Into Recession This Year, Export Credit Agency Says (2025-07-16)

Events:

1. President Trump imposed tariffs on Canadian imports including 25% on items not covered by USMCA effective March 2025, plus tariffs on steel, aluminum, and autos not produced in the U.S.
2. Canada experienced a rush to export and build stocks before tariff measures took effect, boosting the economy in the first quarter of 2025 with 2.2% annualized growth.
3. Canada's labor market weakened and goods exports plunged as tariffs took a toll in April and May 2025.
4. Statistics Canada estimated industry-level GDP shrank 0.1% in May 2025, matching April's decline, with a plunge in car production and shipments.
5. President Trump announced on approximately July 9, 2025 that he would increase tariffs on Canadian imports to 35% effective August 1, 2025.
6. The Bank of Canada cut interest rates successively through March 2025, then left its policy rate unchanged.

7. Canada experienced a surprise surge in hiring in June 2025 and consumer inflation heated up that month.

8. Export Development Canada released a report on July 16, 2025 forecasting Canada will fall into recession during 2025.

Predictions:

1. Canada will experience a recession during 2025 with two consecutive quarters of declining GDP.
2. Canada's full-year 2025 growth will average 0.8%.
3. Canada will see modest recovery to 1.0% GDP growth in 2026.
4. The Canadian dollar will average about 72 U.S. cents in 2025 and 75 cents in 2026.
5. U.S. growth will decelerate to 1.4% in 2025 and 1.7% in 2026.
6. The Bank of Canada will likely cut rates further in 2025 but hold steady in 2026.
7. Tariffs will continue to be a headwind for Canada because a sizable chunk of Canadian merchandise sold to the U.S. is not compliant with North American free trade regulations.

- story_3647 [central]: High eigenvector centrality (0.839)

Source article: OECD cuts global 2025 growth forecast to 2.9% on tariffs (2025-06-03)

Events:

1. The world economy grew by 3.3% in 2024.
2. In March 2025, the OECD forecast global growth of 3.1% for 2025 and 3% for 2026.
3. After March 2025, President Donald Trump launched a wave of tariffs that rattled financial markets.
4. In April 2025, Trump imposed a baseline tariff of 10% on imports from around the world and unveiled higher tariffs on dozens of countries, pausing them until July to allow time for negotiations.
5. Trump imposed 25% tariffs on cars and plans

to raise tariffs on steel and aluminium to 50% on June 4, 2025.

6. On June 3, 2025, the OECD slashed its global growth forecast to 2.9% for both 2025 and 2026, warning that Trump's tariffs will stifle the world economy.

Predictions:

1. The world economy will expand by 2.9% in 2025 and 2026.
2. The US economy will grow by just 1.6% in 2025 and slow further to 1.5% in 2026.
3. US inflation will accelerate to just under 4% by the end of 2025.

4. China's economy will grow by 4.7% in 2025.
5. Japan's economy will grow by 0.7% in 2025.
6. The euro zone economy will grow by 1% in 2025.
7. If additional tariffs are introduced, they will further reduce global growth prospects and fuel inflation.

- story_14759 [central]: High eigenvector centrality (0.833)

Source article: OECD cuts global growth forecast to 2.9% in 2025 and 2026 amid escalating trade war (2025-06-03)

Events:

1. The global economy grew by 3.3 percent in 2024 worldwide.
2. In March 2025, the OECD projected global growth of 3.1 percent for 2025 and 3.0 percent for 2026.
3. After March 2025, President Trump launched a series of tariffs that unsettled global financial markets.
4. In April 2025, Trump introduced a baseline 10-percent tariff on global imports and announced increased tariffs on various countries with implementation delayed until July for negotiations.
5. On June 3, 2025, the OECD lowered its global economic growth forecast to 2.9 percent for both 2025 and 2026, citing the impact of Trump's tariff policies.
6. The OECD revised its 2025 US growth projection from 2.2 percent down to 1.6 percent, with further deceleration expected to 1.5 percent in 2026.
7. The effective tariff rate on US merchandise imports soared from two percent in 2024 to 15.4 percent, its highest level since 1938.
1. The world economy will grow by just 2.9 percent in both 2025 and 2026.
2. The US economy will grow by 1.6 percent in 2025 and decelerate further to 1.5 percent in 2026.
3. Weakened economic prospects will be felt around the world with almost no exception, with lower growth and less trade hitting incomes and slowing job growth.
4. Policy uncertainty will dent household consumption and business investment growth in the US.
5. Inflation across G20 economies will moderate to 3.6 percent in 2025 and 3.2 percent in 2026.
6. US inflation will climb to just under four percent by the end of 2025, twice the Federal Reserve's target rate.
7. China's growth will be 4.7 percent in 2025.
8. Japan's growth will be 0.7 percent in 2025.
9. The eurozone will experience one-percent growth.
10. If protectionism and trade policy uncertainty increase further with additional trade barriers, additional tariffs will further reduce global growth prospects and fuel inflation, dampening global growth even more.

Predictions:

- story_17011 [central]: High eigenvector centrality (0.818)

Source article: IMF trims 0.5 percentage point off earlier outlook: Forecast for Australian growth cut (2025-04-23)

Events:

1. On April 2, 2025, US President Donald Trump announced 'Liberation Day' tariffs on most trading partners, raising tariffs on Chinese goods to 145 percent, triggering a global trade war as China and other nations responded with retaliatory tariffs including 125 percent tariffs on US goods.
2. After US government bond yields surged following the initial tariff announcement, Trump announced a lower immediate 10 percent baseline tariff against most countries and a 90-day pause to review the substantially higher duties.
3. On April 7, 2025, Treasury released its initial tariff analysis publicly, estimating the direct impact of global tariffs could trim only 0.1 of a percentage point off local GDP and add 0.2 of a percentage point to inflation.
4. On Monday, April 21, 2025 (Tuesday AEDT), Trump made comments that cast renewed doubt over the future of US Federal Reserve chairman Jerome Powell and Fed indepen-

dence, triggering a renewed selloff in global shares and the US dollar.

5. On April 23, 2025, the International Monetary Fund cut its growth forecast for the Australian economy by half a percentage point to 1.6 percent for 2025, down from 2.1 percent tipped in January, and warned of rising risks to financial stability due to Trump's trade war.

Predictions:

1. The IMF predicts domestic inflation will dip to 2.5 percent in 2025 and rebound to 3.5 percent in 2026 when temporary government energy price subsidies expire.
2. Money markets expect the Reserve Bank of

Australia to cut interest rates at its next board meeting on May 20, 2025.

3. The IMF predicts global growth will slow sharply to just 2.8 percent in 2025, well below the average of 3.7 percent between 2000 and 2019.
4. The IMF predicts economic growth in China will slow to 4 percent in 2025, below President Xi Jinping's 5 percent target.
5. The IMF predicts US economic growth will slow to 1.8 percent in 2025, 0.9 percentage points below the estimate in January.
6. The IMF warns that protectionism will prop up inefficient businesses, reduce competition, stifle innovation and hurt productivity in the medium term.

- story_10204 [coverage] (centrality 1.0000): Covers 68.8% of community (1000/1453 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 4. Negotiation Deadlines and Trade Deal Framework Development

Community id 3; size 1,206 stories.

Metric	Value
Nodes	1,206
Edges	541,173
Density	0.7448
Average degree	897.47
Average similarity	3.5430
Min similarity	1.2800
Max similarity	39.130
Clustering coefficient	0.8693

Characterization. This community tracks the diplomatic negotiation process and evolving deal structures, particularly the 90-day windows and August 1 deadlines for bilateral agreements. It distinctively focuses on the procedural aspects of trade negotiations, including the letters sent to countries, the framework agreements reached (UK, Vietnam, China), and Trump's shifting deadlines, highlighting the gap between promised "90 deals in 90 days" and actual outcomes.

Key events.

- On January 20, 2025, hours after his inauguration, Trump announced 25 percent import tariffs on Canada and Mexico starting in early February because the countries had not done enough to prevent drugs and immigrants from entering the United States.
- On April 9, 2025, Trump reversed his decision and announced all countries would maintain tariffs at 10 percent for 90 days until July 9 to give countries time to negotiate better deals, but excluded China from this arrangement.
- In May 2025, Britain and the United States reached a framework agreement where Britain would impose a general 10 percent tariff on imports to the US with relief on steel, aluminum, and cars, and Britain eliminated some tariffs on certain US products.
- On Saturday July 12, 2025, Trump announced he would impose 30 percent import tariffs on the EU taking effect at the beginning of August unless the parties reach a trade agreement before then to address the US trade deficit.
- During the week ending July 9, 2025, Trump sent more than 20 customs letters to US trading partners announcing planned import tariffs with a negotiation period until August 1 to give countries time to negotiate better terms.

Key predictions.

- Dozens of countries will face reciprocal tariffs if they don't strike trade deals with the U.S. by Aug. 1, 2025.
- Brazil will face 50% tariffs starting Aug. 1, 2025, unless it makes a deal with the Trump administration.
- Canadian products will face 35% tariffs on Aug. 1, 2025, although there are exceptions for goods that comply with the U.S.-Mexico-Canada Agreement.
- Japan and South Korea will face 25% tariffs on Aug. 1, 2025, unless they secure trade deals with the U.S.
- A federal appeals court will hear arguments on July 31, 2025, regarding Trump's authority to impose tariffs, which could result in reversal of some duties already in place.

Representative stories.

- story_2589 [central]: High eigenvector centrality (1.000)

Source article: Trump's six-month tariff circus has resulted in three trade agreements (2025-07-13)

Events:

1. On January 20, 2025, hours after his inauguration, Trump announced 25 percent import tariffs on Canada and Mexico starting in early February because the countries had not done enough to prevent drugs and immigrants from entering the United States.
2. A couple of days after the January 20 announcement, Trump suspended the tariffs on Canada and Mexico for 30 days.
3. In February 2025, Trump imposed a 10 percent import tariff on China, announced 25 percent tariffs on steel and aluminum, and announced unspecified tariffs on cars to increase corporate production in the United States.
4. In early March 2025, Trump reimposed tariffs on Mexico and Canada and added another 10 percent tariff on China, but suspended most tariffs on Canada and Mexico again a couple of days later due to stock market plunges.
5. In March 2025, Trump's steel and aluminum tariffs went into effect to increase US production.
6. In March 2025, China began responding to Trump's tariffs with its own retaliatory tariffs, and the EU outlined billions of dollars in retaliatory tariffs because Trump had imposed tariffs on them.
7. In early April 2025, Trump imposed sweeping tariffs on nearly every country in the world with a 10 percent general tariff plus additional tariffs on some countries to address the US trade deficit, and China increased its retaliatory measures to which Trump responded with even higher tariffs.
8. On April 9, 2025, Trump reversed his decision and announced all countries would maintain tariffs at 10 percent for 90 days until July 9 to give countries time to negotiate better deals, but excluded China from this arrangement.
9. In April 2025, Trump declared the US trade deficit a national emergency to justify imposing tariffs on almost all countries in the world.
10. In May 2025, the United States and China reached an interim agreement where the US lowered its tariffs on China to 30 percent and China lowered its import tariffs on the US to 10 percent after tariffs between the two countries had peaked at triple digits.
11. In May 2025, Britain and the United States reached a framework agreement where Britain would impose a general 10 percent tariff on imports to the US with relief on steel, aluminum, and cars, and Britain eliminated some tariffs on certain US products.
12. In June 2025, Trump raised his steel and aluminum tariffs to 50 percent, citing trade practices that undermine national security.
13. In early July 2025, Trump signed a trade deal with Vietnam subjecting Vietnam to 20 percent import tariffs.
14. On Saturday July 12, 2025, Trump announced he would impose 30 percent import tariffs on the EU taking effect at the beginning of August unless the parties reach a trade agreement before then to address the US trade deficit.
15. During the week ending July 9, 2025, Trump moved the deadline for higher tariffs to early August instead of sticking to the original July 9 deadline because only three actual agreements had been made with Britain, Vietnam, and China, far from the boasted '90 deals in 90 days.'
16. During the week ending July 9, 2025, Trump sent more than 20 customs letters to US trading partners announcing planned import tariffs with a negotiation period until August 1 to give countries time to negotiate better terms.

Predictions:

1. The EU tariffs will take effect at the beginning of August 2025 unless the EU and US reach a trade agreement before then that would lower the tariffs.

- story_9533 [central]: High eigenvector centrality (0.995)

Source article: Where Things Stand With Trump's Tariffs; Many countries are set to face higher tariffs

on Aug. 1, after months of delay (2025-07-11)

Events:

1. On April 2, 2025, President Trump announced reciprocal tariffs as high as 125% on China and applied them to more than 80 nations to pressure countries to negotiate trade deals with the U.S.
2. On April 3, 2025, the Trump administration imposed 25% tariffs on imported vehicles to protect domestic auto industry under national security justifications.
3. On April 9, 2025, President Trump paused the reciprocal tariffs for 90 days after more than 75 countries showed willingness to negotiate regarding trade, trade barriers, tariffs, currency manipulation and other matters.
4. In May 2025, the U.S. Court of International Trade struck down Trump's 10% April 2 tariffs and reciprocal tariffs, ruling that Trump didn't have authority to impose them under the International Emergency Economic Powers Act of 1977.
5. On May 3, 2025, the Trump administration imposed 25% tariffs on auto parts to protect domestic auto industry.
6. In May 2025, President Trump cut additional tariffs on Chinese goods from up to 145% to 30% for 90 days because he sought to facilitate trade negotiations.
7. On June 4, 2025, the Trump administration increased steel and aluminum tariffs from 25% to 50% to protect domestic metal industries, with the U.K. exempt from these tariffs.
8. In June 2025, the U.S. and China reached a tentative trade deal, and Trump maintained the 30% additional tariff rate on Chinese goods.
9. On July 7, 2025, the Trump administration pushed back reciprocal tariffs by three more weeks to August 1, 2025, to allow more time for trade deal negotiations.
10. During the week of July 7, 2025, the Trump administration sent letters to more than a dozen countries including Japan, South Korea, Tunisia, Bosnia and Herzegovina, Indonesia, Bangladesh, Cambodia, Thailand, Serbia, and Brazil, threatening to raise tariff rates unless each secured trade deals with the U.S. by Aug. 1.
11. On July 8, 2025, President Trump announced 50% tariffs on copper imports and 200% tariffs on pharmaceutical imports to reshore supply chains and protect domestic industries.
12. On July 8, 2025, Japan's top trade negotiator said talks with the U.S. had progressed after speaking with U.S. Commerce Secretary Howard Lutnick because both countries sought to reach a trade agreement.

Predictions:

1. Dozens of countries will face reciprocal tariffs if they don't strike trade deals with the U.S. by Aug. 1, 2025.
2. Brazil will face 50% tariffs starting Aug. 1, 2025, unless it makes a deal with the Trump administration.
3. Canadian products will face 35% tariffs on Aug. 1, 2025, although there are exceptions for goods that comply with the U.S.-Mexico-Canada Agreement.
4. Japan and South Korea will face 25% tariffs on Aug. 1, 2025, unless they secure trade deals with the U.S.
5. Trump will soon announce tariffs on semi-conductors.
6. A federal appeals court will hear arguments on July 31, 2025, regarding Trump's authority to impose tariffs, which could result in reversal of some duties already in place.
7. European Union officials will reach a potential trade deal with the U.S. that is expected to retain 10% baseline tariffs for most European goods.

• story_20707 [central]: High eigenvector centrality (0.985)

Source article: Where Things Stand With Trump's Tariffs; Many countries are set to face higher tariffs on Aug. 1, after months of delay (2025-07-11)

Events:

1. On April 2, 2025, President Trump announced reciprocal tariffs as high as 125% on China and applied them to more than 80 nations to pressure countries to negotiate trade deals with the U.S.
2. On April 3, 2025, the Trump administration imposed 25% tariffs on imported vehicles to protect domestic auto industry under na-

tional security justifications.

3. On April 9, 2025, President Trump paused the reciprocal tariffs for 90 days after more than 75 countries showed willingness to negotiate regarding trade, trade barriers, tariffs, currency manipulation and other matters.
4. In May 2025, the U.S. Court of International Trade struck down Trump's 10% April 2 tariffs and reciprocal tariffs because the president didn't have authority to impose them under the International Emergency Economic Powers Act of 1977.
5. On May 3, 2025, the Trump administration imposed 25% tariffs on auto parts to protect domestic auto industry under national security justifications.
6. In May 2025, President Trump cut the additional tariff on Chinese goods from up to 145% to 30% for 90 days after initially imposing the higher rate in April.
7. On June 4, 2025, the Trump administration increased steel and aluminum import tariffs from 25% to 50% to protect domestic metal industries under national security justifications.
8. In June 2025, President Trump and China reached a tentative trade deal and he maintained the 30% additional tariff rate on Chinese goods.
9. On July 7, 2025, the Trump administration pushed back reciprocal tariffs by three more weeks to August 1, 2025, to allow more time for countries to negotiate trade deals with the U.S.
10. During the week of July 7, 2025, the Trump administration sent letters to more than a dozen countries including Japan, South Korea, Tunisia, Bosnia and Herzegovina, Indonesia, Bangladesh, Cambodia, Thailand, and Serbia, threatening to raise tariff rates unless each secured trade deals with the U.S. by Aug. 1.
11. On July 8, 2025, President Trump announced the U.S. would impose 50% tariffs on copper and 200% tariffs on pharmaceuticals, though he gave pharmaceutical companies up to a year and a half to reshore supply chains before the duties come into effect.
12. On July 8, 2025, Japan's top trade negotiator said talks with the U.S. had progressed after speaking with U.S. Commerce Secretary Howard Lutnick because both countries sought to reach a trade deal.
13. On July 8, 2025, President Trump announced he would soon announce tariffs on semiconductors because the Commerce Department had been conducting investigations under Section 232 of the Trade Expansion Act of 1962.

Predictions:

1. Dozens of countries will face reciprocal tariffs if they don't strike trade deals with the U.S. by Aug. 1, 2025.
2. Brazil will face 50% tariffs starting Aug. 1, 2025, unless it secures a trade deal with the U.S.
3. Canadian products will face 35% tariffs on Aug. 1, 2025, although there are exceptions for goods that comply with the U.S.-Mexico-Canada Agreement.
4. European Union officials are nearing a potential trade deal with the U.S. that is expected to retain 10% baseline tariffs for most European goods.
5. Legal challenges to Trump's tariffs could result in a reversal of some of the duties already in place.
6. Arguments regarding the U.S. Court of International Trade ruling on Trump's tariffs are set for July 31, 2025.
7. A bill floated by Sen. Chuck Grassley and Sen. Maria Cantwell would require any tariffs imposed by the president to expire after 60 days unless Congress voted to approve them.

• story_2766 [central]: High eigenvector centrality (0.984)

Source article: How Trump's trade war is upending the global economy (2025-07-08)

Events:

1. On 1 February 2025, President Donald Trump imposed 25% tariffs on Mexican and most Canadian imports and 10% on goods from China to pressure these countries to curb the flow of fentanyl and illegal immigrants into the United States.
2. On 3 February 2025, President Donald Trump suspended his threat of tariffs on Mexico and Canada for 30 days in return for concessions on border and crime enforcement, but the US

- did not reach such a deal with China.
3. On 10 February 2025, President Donald Trump raised tariffs on steel and aluminum to a flat 25% without exceptions or exemptions.
 4. On 3 March 2025, President Donald Trump announced that 25% tariffs on goods from Mexico and Canada would take effect from 4 March and doubled fentanyl-related tariffs on all Chinese imports to 20%.
 5. On 6 March 2025, President Donald Trump exempted goods from Canada and Mexico under a North American trade pact for a month from the 25% tariffs after delaying tariffs on some vehicles built in Canada and Mexico.
 6. On 26 March 2025, President Donald Trump unveiled a 25% tariff on imported cars and light trucks.
 7. On 2 April 2025, President Donald Trump announced global tariffs with a baseline of 10% across all imports and significantly higher duties on some of the US' biggest trading partners.
 8. On 9 April 2025, President Donald Trump paused for 90 days most of his country-specific tariffs following an upheaval in financial markets that erased trillions of dollars from bourses around the world, but kept the 10% blanket duty on almost all US imports in place and raised the tariff on Chinese imports to 125% from 104%, pushing extra duties on Chinese goods to 145%.
 9. On 13 April 2025, the US administration granted exclusions from steep tariffs on smartphones, computers and some other electronics imported largely from China.
 10. On 4 May 2025, President Donald Trump imposed a 100% tariff on all movies produced outside the US.
 11. On 9 May 2025, President Trump and British Prime Minister Keir Starmer announced a limited bilateral trade agreement that left in place 10% tariffs on British exports, modestly expanded agricultural access for both countries and lowered prohibitive US duties on British car exports.
 12. On 12 May 2025, the US and China agreed to temporarily slash reciprocal tariffs under a 90-day truce, with the US cutting extra tariffs on Chinese imports to 30% from 145% and China slashing duties on US imports to 10% from 125%.
 13. On 23 May 2025, President Donald Trump announced he was recommending a straight 50% tariff on goods from the European Union starting on 1 June and warned Apple it would face 25% tariff if phones it sold in the US were manufactured outside of the country.
 14. On 25 May 2025, President Trump backpedaled on his threat to slap 50% tariffs on EU imports, agreeing to extend the deadline for talks until 9 July.
 15. On 28 May 2025, a US trade court blocked President Trump's tariffs from going into effect in a sweeping ruling that the president overstepped his authority by imposing across-the-board duties on imports from US trade partners, which the Trump administration said it would appeal.
 16. On 29 May 2025, a federal appeals court temporarily reinstated the most sweeping of President Trump's tariffs, pausing the lower court's ruling to consider the government's appeal.
 17. On 3 June 2025, President Trump signed an executive proclamation activating a hike in the tariffs on imported steel and aluminum to 50% from 25%.
 18. On 3 July 2025, President Trump announced the US would place a 20% tariff on many Vietnamese exports, with trans-shipments from third countries through Vietnam facing a 40% levy.
 19. On 6 July 2025, President Trump announced on Truth Social that countries aligning themselves with the 'Anti-American policies' of BRICS would be charged an additional 10% tariff.
 20. On 7 July 2025, President Trump announced on Truth Social that additional higher duties announced in earlier months would kick in with delay on 1 August as the US closes on completion of several trade deals, and in letters sent to 14 countries including Japan, South Korea and Serbia, he announced he would introduce tariffs between 25% and 40% from 1 August.
- Predictions:*
1. Additional higher duties announced in earlier months will kick in on 1 August 2025 as the US closes on completion of several trade deals, with tariffs between 25% and 40% being introduced for 14 countries including Japan, South Korea and Serbia.

- story_6261 [central]: High eigenvector centrality (0.949)

Source article: Donald Trump's Tariff blitz: A month-by-month look at the trade moves shaking global markets (2025-07-08)

Events:

1. Donald Trump returned to office as US President on January 20, 2025, and launched an aggressive tariff campaign targeting multiple countries and sectors to implement his 'America First' trade doctrine.
2. On February 1, 2025, Trump imposed 25% tariffs on most Mexican and Canadian imports and 10% on Chinese goods, citing national security concerns over fentanyl trafficking and illegal immigration.
3. On February 3, 2025, Trump paused the tariffs on Mexico and Canada for 30 days after the two countries secured border enforcement concessions, but China remained excluded from any deal.
4. On February 10, 2025, Trump raised tariffs on steel and aluminium imports to a flat 25% across the board with no exemptions.
5. On March 3, 2025, Trump reinstated the 25% tariffs on Canada and Mexico and increased fentanyl-related tariffs on all Chinese imports to 20%.
6. On March 26, 2025, Trump unveiled a 25% tariff on imported cars and light trucks, deepening tensions with global automakers.
7. On April 2, 2025, Trump introduced a 10% blanket duty across almost all U.S. imports with higher tariffs on key trade partners.
8. On April 9, 2025, following massive market disruptions and a \$3 trillion drop in global equities, Trump paused most country-specific tariffs for 90 days but retained the 10% universal tariff and surged Chinese import duties to 145%.
9. On April 13, 2025, the US granted temporary exclusions for smartphones, computers, and key electronics, particularly from China.
10. On April 22, 2025, the administration launched national security probes into pharmaceutical and semiconductor imports under Section 232 of the Trade Act.
11. On May 4, 2025, Trump imposed a 100% tariff on all foreign films, triggering alarm across the entertainment industry.
12. On May 9, 2025, Trump and UK Prime Minister Keir Starmer announced a limited trade agreement maintaining existing 10% tariffs on British exports.
13. On May 12, 2025, the US and China achieved a temporary breakthrough with reciprocal tariff reductions, with US duties dropping from 145% to 30% and China reducing its levies from 125% to 10%.
14. On May 23, 2025, Trump announced a planned 50% tariff on EU goods starting June 1 and threatened Apple with 25% duties if its products continued to be manufactured abroad.
15. Between May 25-29, 2025, a U.S. trade court blocked the sweeping tariffs citing executive overreach, but a federal appeals court reinstated the most controversial tariffs temporarily.
16. On June 3, 2025, Trump signed an executive order doubling tariffs on steel and aluminium to 50%.
17. On July 3, 2025, Trump imposed a new 20% tariff on many Vietnamese exports and hit trans-shipped goods through Vietnam with a 40% levy.
18. On July 6, 2025, Trump declared that countries aligning with the BRICS bloc and their 'anti-American policies' would face an additional 10% tariff.
19. On July 7, 2025, Trump announced that all additional tariffs would come into force on August 1, 2025, and sent letters to 14 countries warning of tariffs ranging between 25% and 40%.

Predictions:

1. The increasing costs of imported goods may fuel inflation, disrupt supply chains, and deepen geopolitical rifts.
2. Trump's tariff policies risk pushing the global economy into a new era of protectionism and instability.

- story_20580 [coverage] (centrality 0.9248): Covers 98.1% of community (1183/1206 nodes)

Source article: TACO or tariffs? Trump's big trade deadline is coming. Here's what to expect (2025-07-24)

Events:

1. President Donald Trump announced reciprocal tariffs on dozens of countries in the Rose Garden on April 2, 2025, which he called 'Liberation Day', planning to levy tariffs including 50% on Brazil and 30% on the European Union with a 10% baseline for all countries.
2. Trump paused the first tariff deadline of April 9, 2025, for 90 days until July 9, 2025, after the announcement caused significant turbulence in financial markets and economists warned of a potential recession.
3. Trump extended the tariff deadline from July 9 to August 1, 2025, on July 7, stating that several countries were negotiating deals.
4. Trump began sending letters to countries on July 7, 2025, notifying them of updated tariffs and warning that retaliatory tariffs would result in even higher U.S. tariffs, with the first batch going to 14 countries including South Africa and Malaysia.
5. Trump sent tariff letters to another eight countries including Brazil on July 9, 2025, bringing the total to 25 tariff letters by July 23, 2025.
6. The United Kingdom became the first country to reach a trade agreement with the United States.
7. Trump announced a trade deal with Japan on July 22, 2025, under which the United States would impose a 15% tariff on Japanese imports instead of the previously threatened 24%, with Japan agreeing to invest \$550 billion in the United States and open its market to U.S. vehicles, rice, and agricultural products.
8. Trump imposed 25% tariffs on nearly all goods from Canada and Mexico ten days after taking office via executive order, citing the need to force the countries to stem the flow of migrants and fentanyl across the U.S. border, while hitting China with a 10% tariff.
9. Canada and Mexico immediately responded with retaliatory tariffs of their own after Trump imposed the 25% tariffs.
10. Trump agreed to a 30-day pause on the Canada and Mexico tariffs two days after imposing them.
11. Trump waived tariffs in March 2025 on goods compliant with the United States-Mexico-Canada Agreement (USMCA) and imposed 25% universal tariffs on steel, aluminum, and automotive imports, including those from Mexico and Canada.
12. Trump raised tariffs on steel, aluminum, and copper to 50% in June 2025, with Canada being the biggest supplier of steel and aluminum to the United States, while automotive import tariffs remained at 25%.
13. Trump sent a letter to Canadian Prime Minister Mark Carney in July 2025 stating he planned to impose 35% across-the-board tariffs on imports from Canada starting August 1, 2025, citing fentanyl issues, trade barriers, and unsustainable trade deficits.
14. Trump sent a letter to Mexican President Claudia Sheinbaum acknowledging Mexico's help in securing the border but stating Mexico had not stopped the cartels trying to turn North America into a narco-trafficking playground.
15. The United States and China called a truce in May 2025 after months of tit-for-tat tariffs that saw U.S. tariffs spike to 145% and Chinese tariffs reach 125%, agreeing to a 90-day suspension of levies set to expire on August 12, 2025.
16. Trump announced on June 11, 2025, that a deal with China had been 'done' subject to final approval by both leaders, with U.S. tariffs set at 55% on imported Chinese goods and China's tariffs remaining at 10%.

Predictions:

1. The August 1, 2025 tariff deadline will arrive with countries facing steep tariffs including 50% on Brazil and 30% on the European Union unless deals are reached.
2. There may be another extension of the August 1 deadline despite Trump's statements that there will be no change.
3. Treasury Secretary Scott Bessent will meet his Chinese counterpart on July 28, 2025 in Stockholm, Sweden, and will likely work out an extension of the China tariff suspension deadline.
4. If countries revert to the steep tariffs originally proposed after the deadline, the higher tariff level will put more pressure on those countries to come with better agreements.

Narrative 5. Automotive Industry Response and Production Relocation Strategies

Community id 4; size 1,169 stories.

Metric	Value
Nodes	1,169
Edges	216,877
Density	0.3177
Average degree	371.05
Average similarity	2.5836
Min similarity	1.2800
Max similarity	31.328
Clustering coefficient	0.6980

Characterization. This community examines how global automakers responded to the 25% vehicle tariffs implemented April 3, 2025, with specific focus on corporate strategies like price freezes, production shifts, and supply chain adjustments. It distinctively details individual company responses (Hyundai’s price freeze through June 2, Toyota’s internal freeze decision, Ferrari’s 10% increase) and manufacturing relocation plans to US facilities, highlighting the industry-specific impact on a sector facing tariffs on both finished vehicles and parts.

Key events.

- The U.S. government implemented a 25 percent tariff on imported cars on Thursday, April 3, 2025 (local time) in the United States.
- Hyundai Motor Group’s U.S. subsidiary announced on Friday, April 4, 2025 (local time) that it would not raise manufacturer’s suggested retail prices of currently sold models for the next two months until June 2, 2025 in the United States to support consumers and protect their purchasing power.
- President Trump announced on April 29, 2025, that he would reduce duties on imported parts used in U.S.-made cars and drop plans to stack metals and other tariffs on top of foreign auto levies.
- General Motors cancelled the release of its first-quarter financial results and withdrew its full-year guidance on April 29, 2025, after news of the tariff changes because the guidance did not account for tariffs.

- Following Trump's tariff imposition, Jaguar Land Rover and other carmakers halted shipments or held their cars in ports while Stellantis suspended production at plants in Mexico and Canada.

Key predictions.

- Major automakers will raise vehicle prices in the United States eventually after holding prices for a few months because tariffs totaling trillions of won are nearly 30 percent of their combined annual operating profit and they cannot absorb these costs indefinitely.
- Automakers will opt for small price hikes on existing models and more significant increases for refreshed or newly launched models in the United States in the coming months to gradually pass tariff costs to consumers while minimizing backlash.
- The new tariffs will raise U.S. vehicle retail prices by anywhere from \$2,500 to \$20,000 in the United States due to the 25 percent tariff on imported cars and components.
- Analysts at S&P Global predict 700,000 fewer cars will be sold in the US in 2025, representing one of the largest forecast adjustments since the 2008 financial crisis and the pandemic pause in manufacturing.

Representative stories.

- story_19394 [central]: High eigenvector centrality (1.000)

Source article: Global automakers diverge on U.S. tariff response (2025-04-07)

Events:

1. The U.S. government implemented a 25 percent tariff on imported cars on Thursday, April 3, 2025 (local time) in the United States.
2. Hyundai Motor Group's U.S. subsidiary announced on Friday, April 4, 2025 (local time) that it would not raise manufacturer's suggested retail prices of currently sold models for the next two months until June 2, 2025 in the United States to support consumers and protect their purchasing power.
3. Toyota Motor Corp. decided internally to freeze vehicle prices in the United States for the time being after the tariff implementation to avoid consumer backlash.
4. Ferrari S.p.A. announced a 10 percent price increase for U.S.-bound vehicles in response to the tariffs because it is a premium brand with less reliance on the U.S. market.
5. Volkswagen AG informed U.S. dealers earlier in April 2025 that it plans to add import surcharges in response to the tariffs in the United States because its U.S. sales are modest compared to Europe and China.
6. Hyundai Motor Group announced plans in March 2025 to increase its annual U.S. production from 700,000 to 1.2 million units in the United States to mitigate tariff impacts as part of its mid-to-long-term strategy.
7. General Motors announced on Thursday, April 3, 2025 that it would expand pickup truck production in Fort Wayne, Indiana in the United States to mitigate tariff impacts.
8. Jaguar Land Rover Automotive PLC tem-

porarily suspended vehicle exports to the United States for April 2025 while it finalizes its response to the tariffs.

Predictions:

1. Kia Corp.'s U.S. subsidiary will announce a similar price freeze move to Hyundai Motor Group in the United States soon after April 4, 2025 because it is part of the same corporate group facing similar market conditions.
2. Nissan Motor Co. will relocate part of its production of the Rogue mid-size SUV from its Fukuoka plant to the United States in summer 2025 to mitigate tariff impacts by shifting production stateside.
3. Volvo Group will increase its U.S. production volume by shifting additional models to its local factory in South Carolina in the United States after April 2025 to mitigate tariff impacts.
4. Mercedes-Benz AG will produce tariff-affected models in the United States after April 2025 to mitigate tariff impacts by manufacturing locally.
5. Major automakers will raise vehicle prices in the United States eventually after holding prices for a few months because tariffs totaling trillions of won are nearly 30 percent of their combined annual operating profit and they cannot absorb these costs indefinitely.
6. Automakers will opt for small price hikes on existing models and more significant increases for refreshed or newly launched models in the United States in the coming months to gradually pass tariff costs to consumers while minimizing backlash.
7. Rising component and material costs will push up final vehicle prices in the United States even with expanded local production because many parts and raw materials are still imported and face tariffs.
8. The new tariffs will raise U.S. vehicle retail prices by anywhere from \$2,500 to \$20,000 in the United States due to the 25 percent tariff on imported cars and components.

• story_1494 [central]: High eigenvector centrality (0.990)

Source article: Trump's order to ease tariffs on autos gets cool response from industry (2025-04-30)

Events:

1. U.S. President Donald Trump imposed 25-percent tariffs on car importers in the U.S. on April 3, 2025, causing concerns about inflation, reduced demand, and job losses.
2. The U.S. auto industry lobbied President Trump for relief from the 25-percent tariffs before April 29, 2025, warning the levies would cause inflation, reduced demand for cars, and job losses.
3. President Trump announced on April 29, 2025, that he would reduce duties on imported parts used in U.S.-made cars and drop plans to stack metals and other tariffs on top of foreign auto levies.
4. Canadian auto industry officials responded on April 30, 2025, calling Trump's tariff relief measures token half-measures that would not meaningfully reduce negative impacts.
5. General Motors cancelled the release of its first-quarter financial results and withdrew its full-year guidance on April 29, 2025, after news of the tariff changes because the guidance did not account for tariffs.

Predictions:

1. A tariff on imported auto parts will go into effect on May 3, 2025, unless there is intervention before then.
2. U.S. automakers will receive reimbursement for tariffs on auto parts at 3.75 percent of the value of U.S.-made cars in the first year, 2.5 percent in the second year, and zero in the third year.
3. Tariffs on auto parts will scramble the global automotive supply chain and lead to higher auto prices for consumers, lower sales at dealerships, and more expensive vehicle servicing and repairs.

• story_5958 [central]: High eigenvector centrality (0.982)

Source article: Carmakers' shares mount comeback after Trump signals 'help' for industry amid tariff threats (2025-04-16)

Events:

1. On April 2, 2025, Trump imposed 25 percent tariffs on all imports of foreign cars in the US, excluding some exemptions for Mexico and Canada, causing severe impact on carmaker share prices and throwing globalised supply chains into uncertainty.
2. Following Trump's tariff imposition, Jaguar Land Rover and other carmakers halted shipments or held their cars in ports while Stellantis suspended production at plants in Mexico and Canada.
3. Last week (approximately April 9, 2025), the Trump administration announced a 125 percent levy on Chinese smartphone imports before temporarily exempting them on Friday (April 11, 2025) and later warning these products would be examined as part of a semiconductor investigation.
4. Carmakers lobbied hard for changes to the 25 percent levies on parts, which are set to be implemented from May 3, 2025, warning that the levy could be particularly damaging as parts are sourced globally and some components cannot be made in the US.
5. On Monday, April 14, 2025, Trump signaled in Washington that there would be 'help' for the automotive industry, stating he was looking at something to help car companies and that manufacturers need time before they can start making parts in the US rather than in

countries such as Canada and Mexico.

6. On April 15, 2025, shares of global carmakers rose following Trump's comment, with Toyota and Honda rising 4.8 and 4 percent respectively, Tata Motors gaining 4.5 percent, Hyundai Motors advancing 4.4 percent, Stellantis rising 4.3 percent, and German groups Volkswagen, Mercedes-Benz and BMW up more than 2 percent.

Predictions:

1. Analysts at S&P Global predict 700,000 fewer cars will be sold in the US in 2025, representing one of the largest forecast adjustments since the 2008 financial crisis and the pandemic pause in manufacturing.
2. Analysts at S&P Global predict US manufacturing will take a bigger hit with a decrease of 1.28 million cars in 2025, with further declines anticipated in the next two years.
3. Analysts at Bernstein predict the tariffs will cause a €5.5 trillion (\$38.3 billion) hit to revenues and a €3.7 trillion blow to profits for Japanese automakers even after accounting for mitigation efforts such as raising vehicle prices and selling fewer cars.
4. Analysts at Bernstein expect concerns over car tariffs to persist, given that the first Trump administration took 16 months from initial consideration of auto tariffs to its final decision to not impose them.

- story_11451 [central]: High eigenvector centrality (0.979)

Source article: Car Prices May Be Rising Sharply as Trump's Policy on Parts Starts to Kick In (2025-05-03)

Events:

1. President Trump ordered 25 percent tariffs on imported auto parts in March 2025 as part of his plan to promote domestic manufacturing
2. The United States imposed 25 percent tariffs on imported cars in early April 2025
3. The administration announced on Tuesday that the tariffs were intended to protect national security by incentivizing domestic automobile production and reducing American reliance on imports
4. The United States imposed 25 percent tariffs on imported auto parts on Saturday, May 3, 2025, which could sharply raise prices for new and used vehicles as well as for repairs and insurance

5. Trump modified some of the rules on Tuesday to allow automakers to avoid paying duties on a portion of the components they import for two years
6. General Motors announced on Friday that it was eliminating a third shift at a pickup truck assembly line in Oshawa, Ontario, because of tariffs, eliminating about 700 union jobs and causing parts makers to lay off another 1,200 people
7. General Motors said on Thursday that the tariffs would cost it up to \$5 billion in 2025

Predictions:

1. The tariffs on parts will have a broader impact because even cars made in the United States often have engines, transmissions, bat-

- teries or other components produced in other countries
2. The tariffs are having a ripple effect on the used car market as more people look for affordable alternatives to new cars, increasing demand and prices
3. The tariffs on new auto parts are expected to increase the cost of repairs and insurance premiums because replacement parts will become more expensive
4. Rising car prices will contribute to overall inflation
5. Consumers will still pay more for cars even if the policy succeeds in bringing manufacturing back to the United States because many goods, including lots of auto parts, can often be made much more cheaply in China, Mexico or other countries
6. Automakers and suppliers will take years to relocate assembly lines and are unlikely to commit billions of dollars to domestic manufacturing because of uncertainty about the direction of trade policy
7. Car prices will still rise by thousands of dollars despite the measures providing the industry some relief
8. The financial stress could drive some suppliers out of business, creating parts shortages
9. The tariffs will shrink the supply of less expensive vehicles as nearly 80 percent of cars priced at less than \$30,000 will be subject to 25 percent tariffs
10. Car prices will probably not skyrocket immediately because most carmakers and their dealers have large inventories of cars manufactured before the tariffs took effect

- story_20639 [central]: High eigenvector centrality (0.977)

Source article: Car prices haven't spiked will it last?; Autos Automakers watching tariff battles like hawks (2025-07-17)

Events:

1. In March 2025, President Donald Trump announced plans to impose 25% tariffs on automobiles, prompting consumers to rush to purchase vehicles before the tariffs took effect.
2. On April 3, 2025, the U.S. government issued 25% tariffs on vehicle imports.
3. On April 9, 2025, the Canadian government issued retaliatory 25% tariffs against U.S.-built vehicles, but included loopholes through confidential remission orders for five companies manufacturing vehicles in Canada.
4. In April 2025, new vehicle sales in Canada rose 11.3% compared to a year earlier, reaching \$10.8 billion in total sales, the highest monthly total ever recorded in Canada.
5. In May 2025, the first full month of tariffs, new vehicle sales in Canada continued to grow year-over-year by 5%, and the average price of a vehicle increased 3.2% compared to one year earlier.
6. By late May 2025, GM observed consumer demand waning after the initial surge in April and early May.
7. In the first quarter of 2025, before counter tar-

iffs took effect, U.S.-built vehicles accounted for 41% of all new vehicle sales in Canada, which dropped to 39% in the second quarter after tariffs took effect.

8. During the tariff period, automakers employed various strategies including stockpiling inventory at dealerships, shifting production between plants, spreading costs across models, and some manufacturers like Mazda and Nissan stopped shipping certain models into Canada.

Predictions:

1. Vehicle sales may already be softening as consumer demand wanes after the initial surge.
2. The impact of tariffs will become more apparent in the second half of 2025 as dealerships work through pre-tariff inventories and other cost factors weigh on automakers, leading to price increases.
3. Any trade deal between the U.S. and Canada will likely still leave some level of tariffs in place rather than eliminating them entirely.
4. Some automakers may reduce the number of internal combustion engine vehicles sold in Canada to meet the federal ZEV mandate requiring 20% of 2026 model year fleet sales to be zero-emission vehicles.

- story_18434 [coverage] (centrality 0.9230): Covers 77.1% of community (901/1169)

nodes)

Source article: (News Focus) S. Korean suppliers scramble to respond to looming U.S. auto parts tariffs (2025-04-10)

Events:

1. The Trump administration imposed a 25 percent tariff on imported vehicles last week (early April 2025) in the United States to protect domestic industry, disrupting production planning and investment strategies across the automotive sector.
2. Hyundai Motor Co. announced last week (early April 2025) that it will freeze prices of all new vehicles sold in the United States through early June in the U.S. market to ease consumer concerns over rising costs following the new duties.
3. Trump lowered Washington's reciprocal tariffs on South Korea and other trading partners to 10 percent on Wednesday (U.S. time, approximately April 9, 2025) in the United States as a 90-day pause, while increasing reciprocal duties on China to 125 percent following Beijing's retaliatory move.
4. The South Korean Ministry of Trade, Industry and Energy announced this week (week of April 7, 2025) that it will funnel additional liquidity of 2 trillion won (\$1.35 billion) into the local automotive industry in South Korea to help the industry face headwinds from U.S. tariffs because automobiles are South Korea's top export item to the U.S.
5. South Korean auto parts suppliers are scrambling

to respond as of Friday, April 11, 2025, across South Korea by reviewing possibilities of increasing U.S. production, launching internal task forces, and coordinating strategies with Hyundai Motor Group because the U.S. is set to extend 25 percent tariffs to auto parts beginning May 3, 2025.

Predictions:

1. The United States will extend a 25 percent tariff to auto parts beginning May 3, 2025, in the United States as part of the Trump administration's trade policy, affecting South Korean suppliers by forcing them to increase local U.S. production or absorb costs.
2. Major car manufacturers will likely see a decline in sales due to the U.S. tariffs in the U.S. market in the coming months because of increased costs and reduced competitiveness, with small and medium-sized auto parts manufacturers expected to suffer more serious damage through reduced sales and profitability.
3. Many smaller supplier firms may not survive without price increases in the U.S. market in the near future because they lack the financial resources to absorb tariff-related costs, which would inevitably undermine their competitiveness by making their products more expensive.

Narrative 6. India-US Trade Relations and Bilateral Negotiation Dynamics

Community id 5; size 1,049 stories.

Metric	Value
Nodes	1,049
Edges	179,055
Density	0.3257
Average degree	341.38
Average similarity	2.8409
Min similarity	1.2800
Max similarity	19.373
Clustering coefficient	0.7182

Characterization. This community focuses specifically on the US-India tariff relationship, tracking the 26-27% reciprocal tariff announcements and subsequent bilateral negotiations. It distinctively examines India’s strategic response viewing tariffs as manufacturing opportunities, the potential for production relocation from other Asian countries to India, and the specific negotiation challenges around agricultural market access and the August 2025 deadline for a 25% tariff implementation.

Key events.

- On April 2, 2025, the Trump administration announced a 27% additional tariff on Indian imports into the US as part of reciprocal tariffs based on trade deficit computations.
- On April 4, 2025 (Friday in India, Thursday in the US), the Trump administration recalibrated the reciprocal tariff on India to 26% across a range of commodities starting April 9, 2025, correcting its trade deficit computations.
- On April 9, 2025, US President Donald Trump signed another executive order putting a 90-day pause on the country-specific tariffs (suspending the 26% rate for India) for goods entering for consumption on or after April 10, 2025, until July 9, 2025.
- On Wednesday, July 31, 2025, President Trump announced on Truth Social that imports from India would be subject to a 25 percent tariff effective Friday, August 2, 2025, criticizing India’s trade barriers and purchases of Russian energy and military equipment.
- Following the US tariff announcements, Indian government officials stated they view the reciprocal tariffs on India and other Asian countries as an opportunity for India to scale up its manufacturing capabilities.

Key predictions.

- Manufacturing firms in countries like Vietnam and Thailand may relocate to India to take advantage of lower tariff and incentive benefits compared to the higher US tariffs on their countries.
- India will negotiate and complete the first phase of the US-India bilateral trade agreement by fall of 2025 to minimize negative factors from tariffs in the medium-term.
- The tariffs could encourage businesses to choose other Asian nations for manufacturing operations, blunting India's position as a leading alternative to China.
- If both sides walk away from negotiations, the implications for U.S. businesses and India's economy could be quite severe.

Representative stories.

- story_19633 [central]: High eigenvector centrality (1.000)

Source article: Trump tariffs may force India to review Viksit Bharat playbook (2025-04-05)

Events:

ther if required.

1. On April 2, 2025, the Trump administration announced a 27% additional tariff on Indian imports into the US as part of reciprocal tariffs based on trade deficit computations.
2. On April 4, 2025 (Friday in India, Thursday in the US), the Trump administration recalibrated the reciprocal tariff on India to 26% across a range of commodities starting April 9, 2025, correcting its trade deficit computations.
3. On April 4, 2025, China retaliated against the US by imposing an additional 34% tariff on American imports into China, matching Washington's 34% additional tariffs on Chinese goods and escalating the tariff war.
4. Following the US tariff announcements, Indian government officials stated they view the reciprocal tariffs on India and other Asian countries as an opportunity for India to scale up its manufacturing capabilities.
5. Following the tariff announcements, Indian government officials indicated they are open to introducing new schemes or modifying existing ones to incentivize manufacturing fur-

Predictions:

1. Manufacturing firms in countries like Vietnam and Thailand may relocate to India to take advantage of lower tariff and incentive benefits compared to the higher US tariffs on their countries.
2. India's Atma Nirbhar (self-reliance) policy and production-linked incentive scheme will continue to evolve in response to changes in the external environment and domestic performance lessons.
3. India will negotiate and complete the first phase of the US-India bilateral trade agreement by fall of 2025 to minimize negative factors from tariffs in the medium-term.
4. The final bilateral trade agreement with the US will aim to enhance potential gains for India during the next 5-10 years in the long-term.
5. India will identify opportunities from evolving trading patterns and fill gaps as other countries respond to US tariff increases and US exports face increased duties in retaliating countries.

- story_16427 [central]: High eigenvector centrality (0.985)

Source article: Tariff Turbulence: The ripple effects of Trump's trade policies on Indian exports (2025-05-02)

Events:

1. On April 2, 2025, US President Donald Trump signed an executive order imposing reciprocal tariffs on all imports from all US trading partners, starting at 10% and increasing to country-specific rates (26% for India), to rebalance global trade flows.
2. On April 5, 2025, at 12:01 am EDT, the US applied the initial 10% tariff increase on goods entering US Customs Territory from all trading partners including India.
3. From April 5 to April 9, 2025, the US subjected goods exported from India to 10% tariffs under the executive order.
4. On April 9, 2025, US President Donald Trump signed another executive order putting a 90-day pause on the country-specific tariffs (suspending the 26% rate for India) for goods entering for consumption on or after April 10, 2025, until July 9, 2025.
5. After April 9, 2025, India and the USA began

negotiating a comprehensive trade deal with agreed-upon terms of reference, with India reportedly planning to reduce tariffs on US imports.

Predictions:

1. Indian entities engaged in exports to the USA will need to prepare for an increase in tariffs on exports to the US, as any potential trade deal is unlikely to entirely reverse tariff rates to pre-executive order levels.
2. Entities exporting from India and importing in the USA will review their contracts to examine the implications of increased tariffs, leading to contractual claims and disputes.
3. The Trump Tariffs will have significant ramifications for trade between India and the US, creating confusion and potential disruptions in the supply chain, requiring exporters and importers to renegotiate contracts and navigate complexities to mitigate financial and operational impact.

- story_8799 [central]: High eigenvector centrality (0.971)

Source article: Trump Threatens India With Tariffs, Adding a Penalty Over Russian Oil (2025-07-31)

Events:

1. On April 2, 2025, President Trump announced plans for sweeping tariffs on dozens of countries including a 26 percent tariff threat against India to pressure countries on trade barriers.
2. In recent weeks before July 31, 2025, the United States and India conducted trade negotiations and seemed close to clinching a trade deal, but talks hit obstacles over India opening agricultural and dairy markets and Trump seeking to retain high tariffs even under a trade agreement.
3. On Wednesday, July 31, 2025, President Trump announced on Truth Social that imports from India would be subject to a 25 percent tariff effective Friday, August 2, 2025, criticizing India's trade barriers and purchases of Russian energy and military equipment.
4. On July 31, 2025, India's commerce ministry responded by stating it was studying the im-

plications of Trump's announcement and remained committed to concluding a fair bilateral trade agreement.

5. On Wednesday afternoon, July 31, 2025, President Trump stated that Prime Minister Modi was his friend but India had imposed high tariffs on American goods, and indicated India was willing to cut tariffs substantially but a decision would come by end of week.

Predictions:

1. The 25 percent tariff announcement will put pressure on India to strike a deal or face tariffs that will strain economic and diplomatic ties between the countries by Friday, August 2, 2025.
2. The tariffs could encourage businesses to choose other Asian nations for manufacturing operations, blunting India's position as a leading alternative to China.
3. If both sides walk away from negotiations, the implications for U.S. businesses and India's economy could be quite severe.

- story_15797 [central]: High eigenvector centrality (0.942)

Source article: US farm produce, petrochemicals, medical devices face India's \$1.9 billion retaliatory tariffs (2025-05-13)

Events:

1. In 2018, the Trump administration introduced 25% additional tariffs on steel articles and 10% additional tariffs on aluminium goods, affecting global exporters including India.
2. In 2019, India imposed higher tariffs on 28 US products including almonds and apples after the US ended India's preferential access under the Generalized System of Preferences (GSP) and maintained duties on Indian steel and aluminium.
3. In 2020, the Trump administration extended the steel and aluminium tariffs introduced in 2018.
4. In 2023, India and the US resolved the 2019 tariff dispute following Prime Minister Modi's visit to Washington.
5. On February 10, 2025, Trump extended the 25% additional tariff on steel articles and 10% additional tariffs on aluminium goods with effect from March 12, 2025.
6. On April 9, 2025, Trump announced a 90-day

pause on tariff hikes for major trading partners including India, with a 26% tariff on India, while a 10% base tariff continues to apply during the pause.

7. On May 13, 2025, India informed the World Trade Organization that it will impose \$1.91 billion of levies on imports from the US in retaliation against Trump's extension of safeguard duties on Indian steel and aluminium exports, but left a 30-day window for talks.

Predictions:

1. Commerce minister Piyush Goyal will lead a trade delegation to the US starting May 16 to advance trade negotiations.
2. Unless consultations are initiated or the US measures are withdrawn, India's retaliatory tariffs may come into effect 30 days from the notification date on June 8, 2025.
3. Unless a breakthrough is reached in negotiations, Indian goods exported to the US will face an additional 26% duty across the board once the 90-day pause ends on July 8, 2025.

- story_119 [central]: High eigenvector centrality (0.927)

Source article: India Inc counts the cost with Trump tariffs in place (2025-07-31)

Events:

1. President Donald Trump announced a 25% tariff and an unspecified penalty on Indian goods effective August 1, 2025, citing New Delhi's continued defence and energy ties with Russia, impacting sectors including marine and agricultural products, gems and jewellery, textiles and leather.
2. The US doubled tariffs on steel imports from India from 25% to 50% effective June 4, 2025, under Section 232.
3. The US doubled tariffs on aluminium imports from India from 25% to 50% starting June 4, 2025.
4. The US imposed a 25% tariff on fully assembled passenger vehicles from India effective April 3, 2025.
5. The US introduced a 25% tariff on auto components from India on May 3, 2025.
6. India responded to the US tariffs by proposing retaliatory measures at the WTO.

7. Indian companies across affected sectors began evaluating the potential fallout on their business operations following Trump's announcement.

8. Niranjana Hiranandani called for India to relook its trade policy and diversify trade away from over-reliance on US and China.

9. Harsh Goenka warned on Wednesday evening via tweet that Trump's 25% tariffs would have wide-ranging implications including hits to US exports, MSMEs, jobs, trade surplus, rupee pressure, and slower GDP growth.

Predictions:

1. The 25% tariff will make Indian apparel products 7% to 10% more expensive than competitors and will hurt India's apparel exports to the US starting August 1, 2025.
2. The jewellery sector, which exports over \$9 billion annually to the US, will face serious headwinds due to the 25% tariff.

3. Goods such as dairy, processed food, tea, and marine products will fall into a 25-27% tariff bracket, hurting their price competitiveness in the US and prompting many exporters to explore alternative markets.
 4. Some executives hope that the Modi government and the US trade team will return to the negotiating table following the announcement.
- story_19633 [coverage] (centrality 1.0000): Covers 74.0% of community (776/1049 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 7. EU-US Trade Negotiations and Retaliatory Tariff Preparations

Community id 6; size 719 stories.

Metric	Value
Nodes	719
Edges	172,764
Density	0.6693
Average degree	480.57
Average similarity	3.0699
Min similarity	1.2800
Max similarity	23.867
Clustering coefficient	0.8481

Characterization. This community chronicles the European Union’s collective response to Trump’s 20% tariff threat, emphasizing the shift from comprehensive to slimmed-down deal proposals and preparations for 95 billion in countermeasures. It distinctively focuses on EU unity and strategy evolution, the UK’s separate deal as first-mover, the July 9-14 negotiation crisis, and the bloc’s coordinated approach to potential retaliation versus bilateral negotiations.

Key events.

- On April 2, 2025, Trump unveiled a threat to impose a 20 percent tariff on European goods, which he referred to as ‘Liberation Day’, angering EU officials.
- After April 2, 2025, Trump announced a 90-day pause on the tariff threat to provide time for EU-US trade negotiations.

- In 2020, Britain left the EU, and subsequently became the first country to sign a new trade deal with the Trump administration by caving in to American demands.
- On July 12, 2025, Trump sent a letter threatening to impose a 30 percent tariff rate on the EU from August 1, 2025, delivering a severe blow to Europe's confidence.
- On May 8, 2025, the EU published a list of hundreds of US product lines worth approximately 95 billion which the EU could hit with retaliatory tariffs should negotiations fail.

Key predictions.

- If EU trade ministers agree on July 14, 2025, the EU will enforce a first round of retaliatory tariffs on EUR21.5 billion worth of imports from the US as early as July 15, 2025.
- The EU will consider further countermeasures covering a further EUR70 billion of US goods.
- Negotiations will continue in the weeks ahead before August 1, 2025, and the EU will attempt to negotiate an agreement by that date to avert a trade war.
- The 30% US tariffs on EU imports will severely impact trans-Atlantic trade and supply chains if implemented on August 1, 2025.

Representative stories.

- story_2933 [central]: High eigenvector centrality (1.000)

Source article: News analysis; EU faces critical choice amid Trump's tariff salvo (2025-07-14)

Events:

1. On April 2, 2025, Trump unveiled a threat to impose a 20 percent tariff on European goods, which he referred to as 'Liberation Day', angering EU officials.
2. After April 2, 2025, Trump announced a 90-day pause on the tariff threat to provide time for EU-US trade negotiations.
3. After the 90-day pause announcement, the EU conducted confidential trade negotiations with the US behind closed doors, seeking a comprehensive agreement.
4. In 2020, Britain left the EU, and subsequently became the first country to sign a new trade deal with the Trump administration by caving in to American demands.
5. On June 5, 2025, EU Trade Commissioner Maros Sefcovic stated at a Brussels conference that the EU was seeking a comprehensive agreement to end all disputes.
6. In the past few weeks before July 14, 2025, the EU switched tactics and proposed a slimmed-down partial deal similar to Britain's, including abolition of a 10 percent duty on US cars and acceptance of a 10 percent across-the-board duty on European products.
7. On July 9, 2025, the EU delivered its slimmed-down proposal to Trump, and Trump initially responded encouragingly by saying the EU had been 'very nice'.
8. On July 12, 2025, Trump sent a letter threat-

ening to impose a 30 percent tariff rate on the EU from August 1, 2025, delivering a severe blow to Europe's confidence.

9. On July 13, 2025, Irish Prime Minister Micheal Martin expressed hope that negotiations would continue and be successful.
10. On July 14, 2025, EU trade ministers from 27 member states met in Brussels to decide whether to persist in reaching a trade deal with the US or impose retaliatory tariffs against American products.

Predictions:

- story_2568 [central]: High eigenvector centrality (0.968)

Source article: Update EU negotiator: New US tariffs on EU imports would 'prohibit trade' (2025-07-14)

Events:

1. On April 2, 2025, US President Donald Trump announced reciprocal tariffs and implemented a 90-day pause on them.
2. Before Trump's tariff announcement, EU negotiators hoped that they would reach an agreement with Washington on trade.
3. US President Donald Trump announced that he would impose additional 30% tariffs on imports from the European Union effective August 1, 2025, disappointing EU negotiators who thought an agreement was within reach.
4. Recently, Trump sent letters to foreign leaders informing them of steep new tariffs he intends to impose on their goods as of August 1, 2025.
5. On Saturday (approximately July 12, 2025), Trump announced 30% tariffs on Mexico.

1. If EU trade ministers agree on July 14, 2025, the EU will enforce a first round of retaliatory tariffs on EUR21.5 billion worth of imports from the US as early as July 15, 2025.
2. The EU will consider further countermeasures covering a further EUR70 billion of US goods.
3. Negotiations will continue in the weeks ahead before August 1, 2025, and the EU will attempt to negotiate an agreement by that date to avert a trade war.

6. On July 14, 2025, EU Trade Commissioner Maro efovi warned that the announced US tariffs would severely impact trans-Atlantic trade and supply chains.
7. On July 14, 2025, efovi attended a meeting of EU trade ministers in Brussels to discuss possible countermeasures in case negotiations fail.
8. On July 14, 2025, efovi announced new talks with his US counterparts scheduled for later that day.

Predictions:

1. The 30% US tariffs on EU imports will severely impact trans-Atlantic trade and supply chains if implemented on August 1, 2025.
2. The EU will implement countermeasures if negotiations with the US fail.

- story_3435 [central]: High eigenvector centrality (0.963)

Source article: Harris urges tariff exemptions for key sectors (2025-06-11)

Events:

1. On April 2, 2025, President Trump announced 20% reciprocal tariffs on nearly all European goods and sweeping duties on scores of other countries to address trade imbalances.
2. After turbulence on the bond markets, President Trump paused the 20% tariffs for 90 days until July 9, 2025.
3. Following the pause, the European Commission led by Maro efovi and the Trump administration led by Trade Secretary Jamieson

- Greer and Commerce Secretary Howard Lutnick began negotiations to avert the tariffs.
4. Last month (May 2025), President Trump threatened to hit the EU with 50% tariffs, complaining that negotiations were going nowhere.
5. President Trump lifted the 50% tariff threat following a phone call with European Commission President Ursula von der Leyen.
6. On May 8, 2025, the EU published a list of hundreds of US product lines worth approximately 95 billion which the EU could hit with retaliatory tariffs should negotiations fail.

7. The European Commission initiated a four-week consultation period with member states following the publication of the retaliatory tariff list on May 8, 2025.
8. Tánaiste Simon Harris wrote a letter to EU Trade Commissioner Maro efovi urging exemptions for sectors key to the Irish economy from any EU retaliatory tariffs.

Predictions:

1. The EU will implement retaliatory tariffs on US products worth 95 billion if US-EU trade negotiations fail by July 9, 2025.
2. If a trade deal is reached between the EU and US, the EU will not implement the retaliatory tariffs.

- story_2514 [central]: High eigenvector centrality (0.959)

Source article: EU warns Trump's 30% tariffs would eliminate transatlantic trade (2025-07-14)

Events:

1. In April 2025, Trump set reciprocal tariffs at 20% on the EU to address trade imbalances.
2. Trump dropped the tariffs to 10% to allow time for negotiations between the US and EU.
3. On Saturday (July 12, 2025), Trump posted a letter on Truth Social announcing a 30% tariff threat on the EU effective August 1, 2025.
4. On Monday (July 14, 2025), EU trade commissioner Maro efovi warned that 30% tariffs would make transatlantic trade almost impossible and briefed EU trade ministers in Brussels.
5. On Monday afternoon (July 14, 2025), efovi

planned to talk with US commerce secretary Howard Lutnick to push for a deal.

Predictions:

1. If Trump imposes 30% tariffs on August 1, 2025, transatlantic trade between the EU and US will become almost impossible.
2. The EU will propose retaliatory tariffs covering about 72bn of annual US imports to member states.
3. Trump will increase tariffs beyond 30% to match any retaliatory levies by the EU.
4. Transatlantic supply chains will be heavily affected on both sides of the Atlantic if 30% tariffs are imposed.

- story_14744 [central]: High eigenvector centrality (0.946)

Source article: US extends European tariff suspension to July 9 (2025-06-04)

Events:

1. On April 2, 2025, President Donald Trump imposed reciprocal duties of up to 50 percent on 57 trading partners including the EU to address trade imbalances, but he paused them days later to allow negotiations until July 9.
2. On May 19, 2025, the European Commission released a report estimating that US tariff hikes would moderately impact EU GDP but significantly harm the US economy through higher consumer prices, weaker demand, and reduced exports.
3. Before June 1, 2025, President Donald Trump threatened to impose a 50 percent tariff on EU goods, citing stalled negotiations and describing the EU as very difficult to deal with.
4. On June 4, 2025, President Donald Trump

had a phone call with European Commission President Ursula von der Leyen which he described as a very nice call, leading to the tariff postponement decision.

5. On June 4, 2025, the US announced the postponement of the proposed 50 percent tariff on EU goods from June 1 to July 9 to allow additional time for trade negotiations.

Predictions:

1. The EU will impose tariffs on \$107.2 billion of US imports including aircraft, bourbon and agricultural products if negotiations fail by July 9, 2025.
2. US tariff hikes will moderately impact EU GDP but significantly harm the US economy through higher consumer prices, weaker demand, and reduced exports.

- story_3965 [coverage] (centrality 0.9100): Covers 94.6% of community (680/719 nodes)

Source article: If US rises tariffs, EU must respond in same way - Lipavsky (2025-05-25)

Events:

1. In early April 2025, US President Donald Trump unveiled sweeping reciprocal tariffs with a minimum rate of 10 percent on most goods imported into the US and imposed a 20 percent tariff on imports of EU products to pressure countries into bilateral agreements.
2. The day after the tariffs began in April 2025, Trump lowered the reciprocal rate to 10 percent for most countries, effective immediately for 90 days, to allow countries to conclude bilateral agreements with the US during this pause.
3. In response to Trump's tariff reduction and 90-day pause in mid-April 2025, the European Commission postponed for 90 days the countermeasures against US tariffs that were due to take effect on April 15, which would have imposed a 25 percent tariff on a wide range of US exports.

4. On Friday, May 23, 2025, US President Donald Trump announced that he would recommend a 50 percent tariff on imports from the EU from June 1 because the current negotiations with the EU were going nowhere.
5. On May 25, 2025, Czech Foreign Minister Jan Lipavsky stated on Czech Television's Question Time that if the US launches increased tariffs of 50 percent on EU imports from June, Europe must collectively respond in the same way using its package of retaliatory tariffs ready, while continuing to negotiate until the possible launch.

Predictions:

1. If the US implements 50 percent tariffs on EU imports from June 1, 2025, the European Union will respond with retaliatory tariffs of the same magnitude using its prepared package of countermeasures.

Narrative 8. Southeast Asian Manufacturing Hub Competition and Transshipment Concerns

Community id 7; size 595 stories.

Metric	Value
Nodes	595
Edges	61,554
Density	0.3483
Average degree	206.90
Average similarity	2.7863
Min similarity	1.2800
Max similarity	28.023
Clustering coefficient	0.6611

Characterization. This community examines the impact on Southeast Asian manufacturing economies (Vietnam, Indonesia, Cambodia, Thailand, Philippines), particularly their textile and footwear sectors facing 32-49% tariffs. It distinctively focuses on transshipment allegations, the region's efforts to increase US imports as bargaining chips, competition among ASEAN nations for foreign investment, and the strategic dilemma of balancing relationships between Washington and Beijing.

Key events.

- Vietnam, Indonesia, and Cambodia exported significant volumes of textiles and footwear to the US in 2024, with Vietnam shipping US\$24.5 billion, Indonesia US\$7.1 billion, and Cambodia US\$745.8 million, making these sectors critical to their export economies and employment.
- The US under President Trump announced steep tariff hikes on April 9, 2025, targeting Vietnam with 46%, Cambodia with 49%, and Indonesia with 32% increases, threatening South-east Asia's manufacturing competitiveness.
- President Trump unexpectedly granted a 90-day reprieve and announced a lower 10% blanket tariff for most countries on April 9, 2025, while raising duties on China to 125%.
- In April 2025, Chinese exports to south-east Asia jumped more than 20 percent while US-China trade plunged, with the sharpest rises to Vietnam, Indonesia and Thailand.
- Vietnam offered to bring import tariff rates to 0% for US goods and agreed to start talks for a bilateral trade agreement with the US.

Key predictions.

- The outcome of the 90-day negotiations could determine whether South-east Asia maintains its appeal as a long-term magnet for foreign investment.
- South-east Asia will remain attractive in the long run if countries manage to strike deals with the US and depreciate their currencies to compensate for part of the tariff increases.
- Vietnam stands to lose the most from the tariff hike, with shipments of clothes and shoes expected to bear the brunt of a significant decline in US demand.
- Some south-east Asian countries will be bound to have to make choices between Washington and Beijing.
- If the US pushes to cut Chinese content out of goods originating in south-east Asia, governments will have to make a political calculation and an economic one and may have to explicitly choose between the US and China.

Representative stories.

- story_18139 [central]: High eigenvector centrality (1.000)

Source article: ASEAN BUSINESS; South-east Asia's key garment and footwear trade dodges tariff bullet – for now (2025-04-12)

Events:

1. Vietnam, Indonesia, and Cambodia exported significant volumes of textiles and footwear to the US in 2024, with Vietnam shipping US\$24.5 billion, Indonesia US\$7.1 billion, and Cambodia US\$745.8 million, making these sectors critical to their export economies and employment.
2. The US under President Trump announced steep tariff hikes on April 9, 2025, targeting Vietnam with 46%, Cambodia with 49%, and Indonesia with 32% increases, threatening South-east Asia's manufacturing competitiveness.
3. President Trump unexpectedly granted a 90-day reprieve and announced a lower 10% blanket tariff for most countries on April 9, 2025, while raising duties on China to 125%.
4. ASEAN countries responded by focusing on dialogue with the US and pledging not to impose retaliatory tariffs in efforts to secure relief.
5. Indonesia explored a plan to boost US cotton imports from 17% to 50% of its annual 500,000 tonnes to narrow its US\$17 billion trade surplus with Washington.
6. Cambodia offered an average 10% cut on US imports including meat, dairy products, and motorcycles as a bargaining chip to secure lower duties on its exports.

7. Vietnam offered to bring import tariff rates to 0% for US goods and agreed to start talks for a bilateral trade agreement with the US.
8. Nike reached out directly to the Indonesian government via Zoom call to safeguard its supply chain, which includes at least nine factories in Indonesia employing hundreds of thousands of workers.

Predictions:

1. The outcome of the 90-day negotiations could determine whether South-east Asia maintains its appeal as a long-term magnet for foreign investment.
2. South-east Asia will remain attractive in the long run if countries manage to strike deals with the US and depreciate their currencies to compensate for part of the tariff increases.
3. The trade war is opening the door for reshoring opportunities to Indonesia from countries likely to be hit harder such as Vietnam, Bangladesh, China and Thailand.
4. Vietnam stands to lose the most from the tariff hike, with shipments of clothes and shoes expected to bear the brunt of a significant decline in US demand.
5. Regional manufacturers will race to diversify their customer base, seeking new markets as a long-term strategy to safeguard profit margins and reduce overreliance on the US.

- story_4323 [central]: High eigenvector centrality (0.985)

Source article: Vietnam feels US heat over China trade 'back door' (2025-05-16)

Events:

1. During Trump's first term, production shifted from China to Vietnam, and Vietnam emerged as a manufacturing powerhouse with the third-largest trade surplus with the US after China and Mexico.
2. In early April 2025, Trump imposed 46 percent tariffs on Vietnam on 'liberation day' because US officials singled out Vietnam repeatedly for allowing trans-shipment.
3. After the tariff announcement, the US gave Vietnam a 90-day reprieve from the 46 per-

cent tariffs.

4. In April 2025, Chinese exports to south-east Asia jumped more than 20 percent while US-China trade plunged, with the sharpest rises to Vietnam, Indonesia and Thailand.
5. On Monday May 12, 2025, Washington and Beijing announced a temporary truce in their trade war, with the US agreeing to lower additional tariffs on China to about 30 percent for 90 days.
6. This week (week of May 12, 2025), Prime Minister Pham Minh Chinh told US exec-

utives in a meeting that Washington had stressed trans-shipment in tariff negotiations.

7. Vietnam, Indonesia and Thailand held initial trade talks with the US and vowed to increase purchases of American goods and reduce non-tariff barriers.
8. Since Trump's reciprocal tariff announcement, Indonesia, Thailand and Malaysia promised to increase scrutiny of trans-shipments.

Predictions:

1. Countries in south-east Asia hope for further talks with US trade representative Jamieson

Greer at the Asia-Pacific Economic Cooperation meeting of trade envoys in South Korea this week.

2. Governments in the region will be wary of taking direct action against Chinese companies for fear of angering Beijing.
3. Some south-east Asian countries will be bound to have to make choices between Washington and Beijing.
4. If the US pushes to cut Chinese content out of goods originating in south-east Asia, governments will have to make a political calculation and an economic one and may have to explicitly choose between the US and China.

• story_4041 [central]: High eigenvector centrality (0.978)

Source article: Economists weigh in on Trump's 20% tariff (2025-07-11)

Events:

1. In April 2025, the Trump administration announced 17 percent reciprocal tariffs on Philippine exports to the US.
2. On or before July 11, 2025, US President Donald Trump decided to increase the tariff on all Philippine exports from 17 percent to 20 percent, effective August 1, 2025.
3. On July 11, 2025, economists and business leaders in the Philippines assessed the impact of the 20 percent tariff and called for government support and policy responses.
4. On July 11, 2025, Trade Secretary Cristina Roque announced that she will travel to the US next week with other officials to negotiate for a lower tariff.

Predictions:

1. Starting August 1, 2025, the US will impose a 20 percent general tariff on all Philippine exports to the US.
2. Local exporters selling to the US market will

see demand shrink as their products become more expensive due to higher tariffs.

3. Some Philippine companies will pivot to alternative markets such as Canada, Europe, or South America.
4. If other countries like Vietnam face higher tariffs, the Philippines could become more attractive as a manufacturing base for industries like electronics or textiles.
5. The tariff risk could fuel inflationary pressures in the Philippines, which may limit the Bangko Sentral ng Pilipinas' ability to cut interest rates.
6. The tariff hike could result in job losses as Filipino exporters may be forced to reduce production if they fail to secure alternative export markets.
7. The higher tariff will erode the price competitiveness of key Philippine export products, especially electronics, garments, and agricultural goods, and will slow manufacturing output and weigh on overall GDP growth.

• story_4033 [central]: High eigenvector centrality (0.974)

Source article: Philippines keeping its cool despite Trump raising tariffs to 20% (2025-07-11)

Events:

1. In 2024, the US became the Philippines' third-largest trading partner and top export market, taking in US\$12.14 billion worth of goods or about 16.6 per cent of total outbound trade, with electronic products accounting for US\$39.09 billion or more than half of total export earnings.

2. In April 2025, US President Donald Trump announced 17 per cent tariffs on Philippine exports as part of his trade policy focused on bilateral trade deficits.
3. On July 7, 2025, Trump issued letters to 14 nations updating them on import duty levels if they fail to negotiate a deal with the United States by August 1.

4. This week (around July 9-10, 2025), Trump raised tariffs on Philippine exports to 20 per cent and sent letters to a second batch of seven nations including the Philippines informing them of the updated tariff levels.
5. On July 10, 2025, Special Assistant to the President Frederick Go held a press briefing in Manila stating that the Philippines is concerned but noting that 20 per cent is the second-lowest tariff in the region and that a large part of semiconductor exports are not covered by the new tariffs.
6. Since May 2025, Philippine and US officials have been conducting negotiations mostly via email after initial face-to-face meetings to discuss tariff relief.

Predictions:

1. Philippine officials will fly to Washington next week (week of July 14, 2025) to negotiate

with US trade representatives to seek tariff relief from the new 20 per cent rate through face-to-face meetings because such meetings are far more effective than email discussions.

2. Other countries will band together and decide to deal with each other more aggressively and isolate or shun the US because Trump's tariff policies reflect a political fixation on bilateral trade deficits.
3. The tariff measures will introduce added uncertainty into global markets, potentially disrupting supply chains and investment sentiment, which will have a huge impact on supply chains globally and many trading sectors including semiconductors.
4. The Philippines will deepen trade ties with China because the US tariffs are giving China the upper hand as more countries trade with China while the US self-isolates.

• story_20183 [central]: High eigenvector centrality (0.974)

Source article: Southeast Asia clobbered by tariffs but US will be hit too (2025-04-02)

Events:

1. Retailers and brands moved production from China to Vietnam in recent years to avoid US trade punishment of China, compounding Vietnam's trade surplus with Washington and growing imports from Vietnam to \$136.6 billion in 2024.
2. Vietnam announced cuts in import duties on US cars, liquefied gas, and agricultural products on March 31, 2025, attempting to negotiate a better deal with the US.
3. The Trump administration imposed massive import tariffs on April 2, 2025 ('Liberation Day'), hitting ASEAN countries with rates ranging from 17% to 49%, with Vietnam at 46%, Thailand at 36%, Cambodia at 49%, Indonesia at 32%, Myanmar at 44%, Laos at 48%, Malaysia at 24%, Philippines at 17%, and Singapore spared above the blanket 10%.
4. Southeast Asian countries reeled from the tariffs on April 3, 2025, with economists warning the tariffs would slow regional economies and impact poverty reduction efforts.
5. Australian Prime Minister Anthony Albanese

slammed the Trump administration during an April 3, 2025 press conference in Melbourne, calling the tariffs 'totally unwarranted' and 'not the act of a friend.'

6. Vietnam's Deputy Prime Minister Ho Duc Phoc prepared to meet White House officials in Washington over the weekend following April 2, 2025, with executives from Vietnam Airlines and Vietjet Aviation meeting counterparts from Boeing and US banks.

Predictions:

1. The tariffs will slow Southeast Asian economies and impact the region's poverty reduction efforts
2. The tariffs will bite US consumers given global brands' reliance on Vietnam's manufacturing sector
3. ASEAN's collective economy will take a painful hit from the tariffs
4. India will try to reduce its 26% tariff further through continued negotiations
5. The situation would become really serious if the US tries to force ASEAN nations to choose between trading only with the US and not China by threatening more punitive tariffs

• story_18139 [coverage] (centrality 1.0000): Covers 81.5% of community (485/595 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 9. UK Government Strategy and Domestic Political Response

Community id 8; size 466 stories.

Metric	Value
Nodes	466
Edges	67,123
Density	0.6195
Average degree	288.08
Average similarity	2.7585
Min similarity	1.2800
Max similarity	22.453
Clustering coefficient	0.7956

Characterization. This community focuses on the British government’s specific response to tariffs, including Downing Street’s defensive strategy, parliamentary consultations on retaliation, and domestic political dynamics. It distinctively emphasizes the UK’s efforts to build relationships with Trump’s administration, the debate over agricultural concessions (beef and chicken), concerns about the car industry’s 25,000 jobs at risk, and the interplay between Starmer’s government and opposition calls for a trade deal.

Key events.

- On Wednesday night (April 2, 2025), Trump unveiled tariffs on countries around the world from the White House rose garden, imposing a 10% baseline tariff on most US imports, 25% on all foreign cars, 20% on EU products, 24% on Japan, and 34% on China.
- On Thursday (April 3, 2025), the US stock market plummeted with the S&P 500 dropping more than 4%, the Nasdaq falling more than 5%, and the Dow Jones falling 2.9% to 41,001.74, wiping approximately €1.5 trillion off US stock values.
- On Thursday (April 3, 2025), Sir Keir Starmer addressed business chiefs in Downing Street, acknowledging Trump’s tariffs would have an ‘economic impact’ and emphasizing the Government would ‘fight’ to strike a trade deal with the US in Britain’s national interest.

- On Thursday (April 3, 2025), Business Secretary Jonathan Reynolds told MPs in the Commons that the UK was launching a request for input on possible retaliatory action, setting a May 1, 2025 deadline for consultation on imposing tit-for-tat tariffs.
- Starmer visited the White House in February 2025 and made the case directly and publicly against including VAT in tariff calculations, successfully persuading the US to exclude it.

Key predictions.

- Thousands of jobs in the UK car industry alone are feared to be under threat after Trump imposed a 25% tariff on all motor imports into America, with experts fearing the move could cost 25,000 jobs in the British car industry.
- If the UK is in a position to agree an economic deal with the US that lifts the tariffs, the UK's request for input on retaliatory action will be paused and any measures flowing from that will be lifted.
- Trump is open to negotiating tariffs with countries that offer something 'phenomenal.'
- Rachel Reeves's fiscal headroom will be wiped out by the impact of tariffs and economic uncertainty.

Representative stories.

- story_7939 [central]: High eigenvector centrality (1.000)

Source article: Stock markets plunge further as Trump tariffs spark chaos but US president insists policy 'going well' (2025-04-04)

Events:

1. On Wednesday night (April 2, 2025), Trump unveiled tariffs on countries around the world from the White House rose garden, imposing a 10% baseline tariff on most US imports, 25% on all foreign cars, 20% on EU products, 24% on Japan, and 34% on China, effective from midnight Washington time (5am Thursday UK time for cars, 5am Saturday for other products), declaring America's 'declaration of economic independence'
2. On Thursday (April 3, 2025), the US stock market plummeted with the S&P 500 dropping more than 4%, the Nasdaq falling more than 5%, and the Dow Jones falling 2.9% to 41,001.74, wiping approximately €1.5 trillion off US stock values, as investors fled risky assets after Trump's tariff announcement
3. On Thursday (April 3, 2025), London's FTSE 100 Index dropped sharply on opening, falling 122.4 points or 1.4% to 8486.09 in the first few minutes of trading in the UK in response to Trump's tariff announcement
4. On Thursday (April 3, 2025), Sir Keir Starmer addressed business chiefs in Downing Street, acknowledging Trump's tariffs would have an 'economic impact' and emphasizing the Government would 'fight' to strike a trade deal with the US in Britain's national interest
5. On Thursday (April 3, 2025), Business Secretary Jonathan Reynolds told MPs in the Commons that the UK was launching a request for input on possible retaliatory action, setting a May 1, 2025 deadline for consultation on imposing tit-for-tat tariffs.

tary Jonathan Reynolds told MPs in the Commons that the UK was launching a request for input on possible retaliatory action, setting a May 1, 2025 deadline for consultation on imposing tit-for-tat tariffs and releasing a list of US products that could be slapped with import taxes

6. On Thursday evening (April 3, 2025), Trump spoke outside Air Force One, claiming his tariffs roll-out was 'going well', the markets would 'boom', and that Sir Keir Starmer was 'very happy' with the 10% tariffs and had taken them 'really well'
7. On Friday (April 4, 2025), global stock markets slid further with London's FTSE 100 dropping 0.68% to 8,416.71, Paris's Cac 40 falling 0.92%, Frankfurt's Dax slipping 0.74%, Tokyo's Nikkei 225 losing 4.3% to 33,263.58, South Korea's Kospi sinking 1.8% to 2,441.86, and Australia's S&P/ASX 200 dropping 2.2% to 7,684.30, as traders remained concerned about the global economic impact

Predictions:

1. Thousands of jobs in the UK car industry alone are feared to be under threat after Trump imposed a 25% tariff on all motor imports into America, with experts fearing the move could cost 25,000 jobs in the British car industry
2. Many countries will likely end up in a recession according to Olu Sonola, head of US economic research at Fitch Ratings
3. The European Union is finalising its first package of countermeasures, with European Commission president Ursula von der Leyen stating 'We are prepared to respond' and warning 'if you take on one of us, you take on all of us'
4. If the UK is in a position to agree an economic deal with the US that lifts the tariffs, the UK's request for input on retaliatory action will be paused and any measures flowing from that will be lifted

• story_7739 [central]: High eigenvector centrality (0.994)

Source article: 'It could've been much worse': how UK avoided a bigger blow from Trump tariffs (2025-04-05)

Events:

1. Trump won the presidential election with tariffs as a central campaign promise, prompting Downing Street to develop a defensive strategy involving building a strong relationship with Trump's White House and launching talks for an economic deal to secure tariff exemptions.
2. Trade talks between the UK and US began soon after Trump's inauguration in January 2025, with the goal of agreeing a relatively narrow deal focused on advanced technologies.
3. Starmer visited the White House in February 2025 and made the case directly and publicly against including VAT in tariff calculations, successfully persuading the US to exclude it.
4. Reynolds visited Washington to meet Howard Lutnick, the US commerce secretary, just over two weeks before Trump's tariff announcement, with UK officials assured they were in a strong position to negotiate.
5. On Thursday, March 27, 2025, less than a week before Trump's announcement, US contacts told UK officials that 'world tariff day means *world* tariff day' and the UK would

be included in the tariffs.

6. On Sunday, March 30, 2025, Trump told reporters aboard Air Force One that tariffs would apply to 'all countries,' causing stock markets across the globe to tumble.
7. Rachel Reeves spoke to US Treasury secretary Scott Bessent before telling the cabinet on Tuesday, April 1, 2025, to brace themselves for tariffs hitting the UK economy.
8. On Wednesday night, April 2, 2025, Jonathan Reynolds and officials watched Trump announce sweeping tariffs, revealing the UK would face a 10% rate while the EU would face 20% and China up to 54%.
9. Starmer hosted business leaders for breakfast on Thursday morning, April 3, 2025, while Reynolds took to the airwaves to project calm and announced in the Commons the first step towards retaliation in case no deal was agreed.

Predictions:

1. Once the tariffs come into force on Saturday, Trump's team will have the bandwidth to return to trade talks with the UK, potentially early next week, initially remotely but could

- quickly return to face-to-face.
2. Trump is open to negotiating tariffs with countries that offer something 'phenomenal.'
 3. The prime minister and chancellor will line up calls with their international counterparts over the weekend to discuss the tariffs and how they plan to respond.
- story_8658 [central]: High eigenvector centrality (0.961)
Source article: Starmer's 11th-hour bid to halt trade war (2025-04-01)
Events:
 1. President Trump announced he would impose tariffs on April 2, 2025 ('Liberation Day'), with his press secretary stating on April 1 evening that he would be open to negotiating exemptions after the levies took effect, because foreign countries have closed markets to US exports and America has been 'ripped off'.
 2. Israel became the first country to give in to Trump's demands on April 1 night when finance minister Bezalel Smotrich signed an order to end tariffs on US imports.
 3. Trump delayed his planned tariff announcement by one hour on April 1 to coincide with Wall Street's close, prompting speculation he wanted to avoid being overshadowed by a stock market sell-off.
 4. The OBR chairman Richard Hughes warned MPs on April 1 that Trump's tariffs and the volatile global environment meant growth forecasts published in last week's Spring Statement would likely be downgraded, wiping out Rachel Reeves's fiscal headroom.
 5. Goldman Sachs downgraded its UK growth forecasts on April 1 from 0.9% to 0.8% for 2025 and from 1.3% to 1.2% for 2026, expecting a larger hit to UK GDP from trade tensions.
 6. The UK government prepared concessions on tariffs for meat (beef and chicken) to persuade Trump to give reciprocal changes, representing a change of tack from Sir Keir Starmer's earlier position in late February that agricultural issues would not be part of discussions.
 7. Tom Bradshaw, president of the National Farmers' Union, demanded on April 1 that British farmers not be short-changed and that any deal must be reciprocal, warning the industry would have a problem with a one-way deal.
 8. Foreign Secretary David Lammy told MPs on April 1 that the UK continues intense conversations with the US administration on getting an economic agreement while preparing for the worst, with all options remaining on the table.*Predictions:*
 1. Trump will announce tariff details at a 'Make America Wealthy Again Event' in the White House Rose Garden at 9pm UK time on April 2, with tariffs of about 20% coming into force immediately.
 2. The UK will be hit by Trump's tariffs as Downing Street has accepted that an agreement will not be struck before April 2.
 3. The OBR will downgrade growth forecasts due to Trump's tariffs and the volatile global environment.
 4. Rachel Reeves's fiscal headroom will be wiped out by the impact of tariffs and economic uncertainty.
 5. Trump's 25% tariff on foreign-made cars will completely destabilize the UK car manufacturing industry and put more than 25,000 UK jobs at risk, particularly at Jaguar Land Rover and Mini.
 6. Further tax rises will likely occur in autumn as the £10 billion fiscal buffer is too small.
 7. If Trump's blanket tariffs trigger tit-for-tat retaliation from other countries, it could escalate into a trade war leading to a downturn, recession in major economies, or even a global recession.
 - story_3641 [central]: High eigenvector centrality (0.949)
Source article: British industry exempted from Trump's doubling of steel tariffs (2025-06-03)

Events:

1. On March 2025, Trump imposed 25 percent tariffs on aluminium and steel imports into the US, impacting UK steel exports worth about €400mn annually to the US market and causing huge uncertainty for British industry including Tata Steel at Port Talbot.
2. On May 8, 2025, Starmer and Trump signed the US-UK Economic Prosperity Deal in a ceremony, promising zero-tariff quotas for UK steel meeting US security requirements excluding China from supply chains and reduced tariffs from 25 to 10 percent on up to 100,000 British car exports, though the document was not legally binding.
3. After May 8, 2025, negotiations over implementing the US-UK trade deal dragged on without conclusion, causing mounting frustration from British industry and creating a credibility issue for Starmer who had over-sold the pact.
4. On June 3, 2025, UK business secretary

Jonathan Reynolds held talks with US counterpart Jamieson Greer in Paris to expedite the trade pact implementation.

5. On June 3, 2025, Trump announced via executive order that the UK would be exempted from a doubling of US steel and aluminium tariffs to 50 percent to allow for implementation of the US-UK Economic Prosperity Deal, though British metal producers would still face the existing 25 percent tax until the pact takes effect.

Predictions:

1. Trump might increase the US tariff on the UK to 50 percent on or after July 9, 2025, leaving steel producers facing huge uncertainty and possibly facing 50 percent tariffs in as little as five weeks' time.
2. The UK will receive zero-tariff quotas for steel and reduced tariffs from 25 to 10 percent on up to 100,000 British car exports once the US-UK Economic Prosperity Deal is implemented.

- story_8250 [central]: High eigenvector centrality (0.932)

Source article: Trump's tariffs will 'clearly have economic impact' in UK Starmer (2025-04-03)

Events:

1. Donald Trump announced sweeping global tariffs including a 10% import tax on British goods, a 20% rate on EU goods, a 24% rate on Japanese goods, a 54% rate on Chinese goods, and a 25% tariff on cars beginning Thursday morning, claiming the tariffs were reciprocal responses to measures by other countries who had 'looted, pillaged, raped, plundered' the US economy.
2. Trump's tariff announcement sent stock markets tumbling globally, with the FTSE 100 Index dropping 122.4 points or 1.4%, the Dax in Germany and Cac 40 in France falling more than 2%, the Nikkei in Japan declining nearly 3%, and China's Hang Seng dropping 1.5%.
3. Prime Minister Sir Keir Starmer gathered business chiefs including Bentley's boss Frank-Steffen Walliser and Jaguar Land Rover's CFO Richard Molyneux in No 10 for talks to address the economic impact of the tariffs on UK exporters who sent €60.4 billion of goods to the US in 2023.

4. Sir Keir Starmer acknowledged the UK would suffer an economic hit from the tariffs and indicated he would fight for a trade deal with the US rather than immediately respond with retaliatory tariffs, though he stressed 'nothing is off the table' and he would only strike a deal if it was in the national interest.
5. Conservative leader Kemi Badenoch urged the Prime Minister to strike a 'deep and meaningful trade deal' with the US, arguing that Trump's tariffs would make everyone poorer and that the Conservatives were ready to help in the national interest.

Predictions:

1. The UK will experience economic impact from Trump's 10% tariff on British goods entering the US, affecting the €60.4 billion of goods the UK exported to the US in 2023.
2. The UK government will continue negotiations on an 'economic prosperity deal' with the US to mitigate the impact of the tariffs.
3. The blanket 10% tariff will come into effect on Saturday (April 5, 2025).

- story_8250 [coverage] (centrality 0.9318): Covers 90.6% of community (422/466 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 10. Energy Markets and Oil Price Collapse Dynamics

Community id 9; size 391 stories.

Metric	Value
Nodes	391
Edges	14,809
Density	0.1942
Average degree	75.749
Average similarity	2.8991
Min similarity	1.2800
Max similarity	25.408
Clustering coefficient	0.6636

Characterization. This community examines the impact of tariffs on global energy markets, particularly the dramatic oil price collapse to four-year lows below \$60/barrel for Brent crude. It distinctively focuses on the intersection of trade war demand destruction with OPEC+ supply increases, the breach of Russia’s price cap for the first time, and energy-specific forecasts showing oil demand growth cut by a third, highlighting commodity market vulnerabilities to trade disruptions.

Key events.

- US President Donald Trump announced sweeping tariffs on most imports, sparking concerns that a global trade war would dent economic growth and hit fuel demand.
- OPEC+ decided last week (early April 2025) to hike output in May by 411,000 barrels per day, a move that analysts say will likely push the market into surplus.
- Russia’s ESPO Blend oil price fell below the \$60 per barrel Western price cap level for the first time ever on Monday, April 7, 2025, as oil prices sank.
- Oil prices fell for a fifth consecutive day to their lowest level since February 2021 on April 9, 2025, with Brent futures dropping to \$61.43 a barrel and US WTI crude futures falling to \$58.08.

- The International Energy Agency cut its oil demand growth forecast for 2025 by about a third from 1.03 million barrels per day to 730,000 b/d in its first forecast since Trump's tariff announcement, published around April 16, 2025.

Key predictions.

- Goldman Sachs forecasts that Brent and WTI could edge down to \$62 and \$58 per barrel by December 2025 and to \$55 and \$51 per barrel by December 2026.
- China's 50,000 bpd to 100,000 bpd of oil demand growth is at risk if the trade war continues for longer.
- OPEC+'s output hike is likely to push the oil market into surplus.
- Annual oil demand growth will slow further in 2026 to 690,000 b/d as lower oil prices only partly offset the weaker economic environment.
- The drop in oil prices will likely slow US oil production growth, as the sell-off has rattled the US shale patch where producers need average prices of at least \$65 a barrel to drill new shale oil wells.

Representative stories.

- story_7091 [central]: High eigenvector centrality (1.000)

Source article: Oil falls to lowest since February 2021 as tariffs hit (2025-04-09)

Events:

1. US President Donald Trump announced sweeping tariffs on most imports, sparking concerns that a global trade war would dent economic growth and hit fuel demand.
2. Beijing failed to lift its retaliatory tariffs on US goods by Trump's deadline on April 8, 2025, prompting Trump to add an additional 50% tariff to the existing 54% tariff on China for a total of 104%.
3. Trump's 104% tariffs on China kicked in overnight on April 9, 2025, escalating the trade war between the world's two biggest economies.
4. Beijing vowed not to bow to US blackmail after Trump threatened the additional 50% tariff on Chinese goods if China did not lift its 34% retaliatory levy.
5. OPEC+ decided last week (early April 2025) to hike output in May by 411,000 barrels per day, a move that analysts say will likely push the market into surplus.
6. Russia's ESPO Blend oil price fell below the \$60 per barrel Western price cap level for the first time ever on Monday, April 7, 2025, as oil prices sank.
7. The American Petroleum Institute reported that US crude inventories fell by 1.1 million barrels in the week ended April 4, 2025, contrary to expectations of a build of about 1.4 million barrels.
8. Oil prices fell for a fifth consecutive day to their lowest level since February 2021 on April 9, 2025, with Brent futures dropping to \$61.43 a barrel and US WTI crude futures falling to \$58.08.

Predictions:

1. Goldman Sachs forecasts that Brent and WTI could edge down to \$62 and \$58 per barrel by December 2025 and to \$55 and \$51 per barrel

by December 2026.

2. China's 50,000 bpd to 100,000 bpd of oil demand growth is at risk if the trade war con-

tinues for longer.

3. OPEC+'s output hike is likely to push the oil market into surplus.

- story_5954 [central]: High eigenvector centrality (0.962)

Source article: Oil demand growth set to slow sharply after Trump tariffs (2025-04-16)

Events:

1. President Donald Trump announced sweeping tariffs on all major US trading partners on April 2, 2025, imposing levies as part of his 'liberation day' announcement, though he exempted imports of oil, gas and refined products from these tariffs.
2. Eight members of OPEC+ led by Saudi Arabia announced on the same day as Trump's tariff announcement (April 2) that they would unwind supply cuts faster than expected from the following month, adding to downward pressure on oil prices.
3. Global markets experienced a rout in the week following the tariff announcement, causing Brent crude prices to dip below \$60 a barrel for the first time in four years.
4. Trump suspended most of the tariffs for 90 days pending negotiations approximately one week after imposing them (around April 9), but simultaneously boosted retaliatory tariffs on China to 125 percent.
5. The International Energy Agency cut its oil demand growth forecast for 2025 by about a third from 1.03 million barrels per day to 730,000 b/d in its first forecast since Trump's tariff announcement, published around April 16, 2025.

6. OPEC cut its oil demand forecast for 2025 by 100,000 b/d on Monday (April 14, 2025), expecting global demand to grow by 1.3 million b/d this year.

Predictions:

1. The IEA signals that further downward revisions to oil demand growth forecasts are possible depending on how Trump's tariff programme evolves, as the situation remains fluid with negotiations and countermeasures still ongoing.
2. Annual oil demand growth will slow further in 2026 to 690,000 b/d as lower oil prices only partly offset the weaker economic environment.
3. The drop in oil prices will likely slow US oil production growth, as the sell-off has rattled the US shale patch where producers need average prices of at least \$65 a barrel to drill new shale oil wells.
4. Trump's tariffs may make it more expensive to buy steel and equipment, further discouraging US drilling activity.
5. Global oil production will likely grow by 1.2 million b/d in 2025, down from a previous forecast of 1.46 million b/d due to the expected slowdown in US shale activity and reduced supply from Venezuela.

- story_19757 [central]: High eigenvector centrality (0.911)

Source article: Oil tumbles 8% as China retaliates with tariffs on US (2025-04-04)

Events:

1. President Donald Trump raised tariff barriers to their highest in more than a century earlier this week
2. China announced on April 4, 2025 that it will impose additional tariffs of 34% on all U.S. goods from April 10 in retaliation to Trump's tariffs
3. OPEC+ advanced plans for output increases, aiming to return 411,000 barrels per day to the market in May, up from the previously planned 135,000 bpd

4. Oil prices plunged by 8% on Friday, April 4, 2025, with Brent futures diving by \$5.30 to \$64.84 a barrel and WTI crude futures losing \$5.47 to \$61.48, heading for their lowest close since 2021
5. Goldman Sachs analysts cut their December 2025 targets for Brent and WTI by \$5 each to \$66 and \$62 respectively in response to the trade war

Predictions:

1. The global trade war will hurt economic growth and demand for key commodities

- such as crude oil and refined products
2. Trump's tariff policies could stoke inflation, slow economic growth and intensify trade disputes, weighing on oil prices
 3. Oil price risks are to the downside, especially for 2026, given growing risks of recession and higher OPEC+ supply

• **story_19878 [central]: High eigenvector centrality (0.900)**

Source article: Oil prices crash over 8% to near 4-year lows amid trade war, Opec supply woes; Brent crude slips below \$65 mark (2025-04-04)

Events:

1. US President Donald Trump imposed tariffs on China and over 180 countries, triggering global trade tensions
2. China announced it will impose additional tariffs of 34% on all US goods from April 10 in retaliation to Trump's levies
3. The Organization of the Petroleum Exporting Countries and its allies (OPEC+) decided to advance plans for output increases, aiming to return 411,000 barrels per day to the market in May instead of the previously planned 135,000 bpd
4. Crude oil prices crashed over 8% on Friday April 4, with Brent futures diving by \$5.72 (8.2%) to \$64.62 a barrel and US West Texas Intermediate crude futures losing \$5.90

(8.8%) to \$61.05, hitting near 4-year lows

5. Goldman Sachs cut their December 2025 targets for Brent and WTI by \$5 each to \$66 and \$62 respectively in response to the market conditions

Predictions:

1. China will impose additional tariffs of 34% on all US goods from April 10
2. OPEC+ will return 411,000 barrels per day to the market in May
3. The trade war policies could stoke inflation, slow economic growth and intensify trade disputes, weighing on oil prices
4. Oil price risks are to the downside, especially for 2026, given growing risks of recession and higher OPEC supply

• **story_18780 [central]: High eigenvector centrality (0.895)**

Source article: Crude oil prices hit four-year low on recession fear, Trump's tariffs, Saudi Arabia's rate cut (2025-04-09)

Events:

1. US President Donald Trump announced sweeping tariffs on most imports over five consecutive sessions prior to April 9, 2025, sparking concerns about a global trade war that would dent economic growth and hit fuel demand.
2. China failed to lift its retaliatory tariffs on US goods by the noon deadline on Tuesday, April 8, 2025, set by Trump, prompting the US to impose a 104% tariff on China from 12:01 a.m. EDT on Wednesday, April 9, 2025.
3. OPEC decided last week (early April 2025) to hike output in May by 411,000 barrels per day, likely pushing the market into surplus.
4. Saudi Arabia announced to increase output and decrease oil prices in early April 2025, contributing to nosediving crude oil prices.
5. Crude oil prices dropped to more than four-year lows on Wednesday, April 9, 2025, with

WTI crude oil price oscillating around \$57.70 and Brent futures falling to \$60.69 a barrel during early morning deals in the Asian stock market.

Predictions:

1. Crude oil prices might continue to trade red and touch the \$52 per barrel mark in the international market, whereas in the domestic market, crude oil prices may test the Rs.5,025 per barrel mark on MCX.
2. Goldman Sachs forecasts that Brent and WTI could edge down to \$62 and \$58 per barrel by December 2025 and to \$55 and \$51 per barrel by December 2026.
3. China's 50,000 bpd to 100,000 bpd of oil demand growth is at risk if the trade war continues for longer, though a stronger stimulus to boost domestic consumption could mitigate the losses.

- story_9208 [coverage] (centrality 0.1994): Covers 45.5% of community (178/391 nodes)

Source article: World News: EU Targets Moscow With Tough Sanctions — Bloc is set to impose new banking, energy bans as it hopes U.S. will do the same (2025-07-19)

Events:

1. Russia launched a large-scale invasion of Ukraine, prompting Western countries to impose sanctions including a \$60 per barrel price cap on Russian oil exports in late 2022.
2. Over the past three years, Russia's economy withstood Western pressure, but Russia deployed a shadow fleet of older uninsured vessels and sold crude to countries like India and Turkey to work around the price cap, reducing its effectiveness.
3. President Trump started increasing pressure on the Kremlin after months of seeking a peace deal between Ukraine and Russia as the White House recognized the Kremlin won't end the war.
4. Nearly two months before July 19, 2025, European leaders threatened to impose a new sanctions package, with German Chancellor Friedrich Merz saying the measures would take effect in days if Putin didn't accept a U.S. cease-fire proposal.
5. On July 19, 2025, the European Union agreed to impose its toughest sanctions on Russia since the invasion, lowering the oil price cap to \$47.60 per barrel, banning Nord Stream pipeline transactions, sanctioning 105 more shadow fleet vessels, banning 22 additional

Russian banks from Swift, and targeting two dozen non-Russian companies including two Chinese regional banks.

6. On July 19, 2025, the U.K. announced it would also adopt the lower price cap, and EU diplomats expected other G-7 countries such as Japan and Canada to join, although Washington said it won't.
7. On July 19, 2025, Ukrainian President Volodymyr Zelensky called the new EU package 'essential and timely' amid intensified Russian attacks on his country.
8. On July 19, 2025, Kremlin spokesman Dmitry Peskov called the package unlawful and said it would hurt European economies.

Predictions:

1. The new oil price cap will be revised every three months to stay 15% below the market price for Russian exports.
2. The sanctions will hit Russian oil giant Rosneft's biggest refinery in India.
3. European capitals hope Washington will soon join them in tightening economic pressure on Moscow.
4. The EU's decision to target Chinese banks adds to growing bilateral strains ahead of next week's EU-China summit.

- story_7091 [coverage] (centrality 1.0000): Covers 31.5% of community (123/391 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 11. Port Traffic Collapse and Supply Chain Disruption

Community id 10; size 352 stories.

Metric	Value
Nodes	352
Edges	22,679
Density	0.3671
Average degree	128.86
Average similarity	2.7083
Min similarity	1.2800
Max similarity	26.182
Clustering coefficient	0.6924

Characterization. This community chronicles the immediate physical disruption to U.S.-China trade flows following Trump’s 145% tariffs in April 2025, focusing on plummeting container ship volumes, port activity collapse at Los Angeles, and cascading effects through logistics and retail sectors. It distinctively emphasizes the tangible, measurable decline in shipping activity and the timeline of when empty shelves and layoffs would materialize.

Key events.

- President Trump raised tariffs on Chinese imports to a minimum of 145 percent in early April 2025, causing trade between the United States and China to grind to a halt.
- The number of massive container ships departing China for the United States plummeted by about a third in April 2025 as companies canceled orders in Chinese factories.
- Sales of heavy trucks fell sharply by late April 2025 as logistics companies anticipated moving fewer goods in the future.
- Major companies including Mercedes-Benz and Stellantis suspended their financial forecasts for 2025 on May 1, 2025, due to trade uncertainty.
- Container ship companies canceled a quarter of all sailings to the United States from China and rerouted ships to Southeast Asia and Europe by early May 2025.

Key predictions.

- The United States will eliminate de minimis treatment for Chinese goods on Friday, May 9, 2025, resulting in higher prices for U.S. consumers and weighing on airlines and private carriers.
- The number of containers arriving at the Port of Los Angeles will drop more than 35 percent in the week of May 11, 2025 compared with the same period last year.
- Consumers will start to see empty shelves and layoffs could occur for retailers and logistics industries by late May or early June 2025.
- The major effects on the U.S. economy of shutting down trade with China will become apparent in summer 2025, when the United States might slip into a recession.
- Even if the Trump administration removes China tariffs and demand resumes, ships will not be in the right location immediately to carry the same volume of goods, resulting in high prices and delays.

Representative stories.

- story_11438 [central]: High eigenvector centrality (1.000)

Source article: West Coast ports face falloff Trump's trade war curbing orders from China, with 35% drop in volume likely soon (2025-05-04)

Events:

1. President Trump raised tariffs on Chinese imports to a minimum of 145 percent in early April 2025, causing trade between the United States and China to grind to a halt.
2. The number of massive container ships departing China for the United States plummeted by about a third in April 2025 as companies canceled orders in Chinese factories.
3. Imports surged at the Port of Los Angeles in recent months before April 2025 as businesses and consumers stockpiled goods in advance of the tariffs coming into effect.
4. As of mid-April 2025, goods coming into the Port of Los Angeles from China became very few and far between, with a quarter of ships scheduled for May canceled due to light volume.
5. Sales of heavy trucks fell sharply by late April 2025 as logistics companies anticipated moving fewer goods in the future.
6. Some companies began raising prices in late April 2025 as the effects of canceled Chinese orders started working through the supply

chain.

7. Major companies including Mercedes-Benz and Stellantis suspended their financial forecasts for 2025 on May 1, 2025, due to trade uncertainty.
8. Container ship companies canceled a quarter of all sailings to the United States from China and rerouted ships to Southeast Asia and Europe by early May 2025.

Predictions:

1. The United States will eliminate de minimis treatment for Chinese goods on Friday, May 9, 2025, resulting in higher prices for U.S. consumers and weighing on airlines and private carriers.
2. The number of containers arriving at the Port of Los Angeles will drop more than 35 percent in the week of May 11, 2025 compared with the same period last year.
3. Container ships with reduced Chinese cargo will start arriving at American ports in late May 2025 as the April shipping decline reaches U.S. shores.
4. Consumers will start to see empty shelves

and layoffs could occur for retailers and logistics industries by late May or early June 2025.

5. The major effects on the U.S. economy of shutting down trade with China will become apparent in summer 2025, when the United States might slip into a recession.
6. If the Trump administration does not reverse

course soon, American consumers will feel the impact of trade changes unfold over the next three to six months from May 2025.

7. Even if the Trump administration removes China tariffs and demand resumes, ships will not be in the right location immediately to carry the same volume of goods, resulting in high prices and delays.

- story_11536 [central]: High eigenvector centrality (0.960)

Source article: A Tidal Wave of Change Is Headed for the U.S. Economy (2025-05-01)

Events:

1. President Trump raised tariffs on Chinese imports to a minimum of 145 percent in early April 2025, causing much of the trade between the United States and China to halt.
2. The number of massive container ships departing China for the United States plummeted by about a third in April 2025 because companies canceled orders in response to the steep tariffs.
3. Imports at the Port of Los Angeles surged in recent months as businesses and consumers stockpiled goods in advance of the tariffs, but this activity started to decline.
4. Companies in the logistics space reduced their expectations for future goods movement, causing sales of heavy trucks to fall sharply.
5. Some companies began raising prices in late April 2025 in response to the tariffs and reduced supply.
6. Some firms in fragile financial positions were rapidly forced out of business because they could not stockpile inventory to weather the tariff increases.
7. Companies froze their plans for expansion and halted new orders, with new orders from manufacturers turning down sharply in 2025.
8. Major companies including Mercedes-Benz and Stellantis suspended their financial forecasts for 2025 on Wednesday due to trade uncertainty.
9. Container ship companies canceled a quarter of all sailings to the United States from China and rerouted their ships to Southeast

Asia and Europe instead.

Predictions:

1. The United States will eliminate de minimis treatment for Chinese goods on Friday May 2, 2025, resulting in higher prices for U.S. consumers and weighing on airlines and private carriers.
2. The number of containers arriving at the Port of Los Angeles will drop more than 35 percent in the week after May 1, 2025 compared with the same period last year.
3. Consumers will start to see some empty shelves and layoffs could occur for retailers and logistics industries by late May or early June 2025.
4. The major effects on the U.S. economy of shutting down trade with China will start to become apparent in the summer of 2025, when the United States might slip into a recession.
5. U.S. consumers will within a few weeks see empty shelves in clothing stores, toy stores, hardware stores and retail drugstores, and higher prices of the goods that still are on the shelves.
6. American consumers will feel the impact of trade changes unfold over the next three to six months if the situation is not changed quickly.
7. If the Trump administration removes its China tariffs and U.S. consumer demand for Chinese products resumes, consumers will see high prices and delays because ships won't be in the right location immediately to carry the same volume of goods.

- story_9914 [central]: High eigenvector centrality (0.958)

Source article: These Ports Are Ground Zero in Trump's Trade War (2025-06-22)

Events:

1. President Trump imposed tariffs to curb foreign trade, causing nearly a fifth of expected ships to cancel arrivals at the Port of Los Angeles in May 2025.
2. Shippers rushed to bring goods into the ports early in 2025 ahead of tariffs that reached their highest levels in a century, causing a surge in port activity.
3. President Trump ratcheted up tariffs on Chinese goods to at least 145 percent in April 2025, causing many shipments between the US and China to halt.
4. US imports and the trade deficit plummeted by the biggest volume on record from March to April 2025.
5. Future bookings to send shipping containers from China to the United States plunged by half from a year earlier during the roughly four weeks that the 145 percent tariffs were in effect.
6. Chinese exports to the United States dropped roughly 35 percent from a year earlier in May 2025, making it the slowest month for the Port of Los Angeles in over two years.
7. President Trump paused some levies in April 2025 so he could negotiate new trade deals,

causing bookings to rebound modestly.

8. The United States and China reached an agreement in early May 2025 to reduce some of the tariffs they specifically targeted against each other.
9. The cost of shipping a container to Southern California from China doubled since the start of March 2025.
10. Erick Gordon's trucking company, Redefined Transportation, let half its drivers go and lowered rates in response to moving roughly half the number of containers compared to the previous year.

Predictions:

1. The port will experience another uptick in traffic as a delayed reaction after the president paused some levies in April 2025.
2. Higher costs for imports will filter more noticeably into prices in stores later in 2025.
3. Consumer demand will weaken later in 2025 as a reaction to rash purchasing in the early months of 2025 before tariffs took effect.
4. The hit to the economy from tariffs will become visible in the next few months after June 2025.
5. Higher tariffs will snap back within weeks after June 2025.

• story_15709 [central]: High eigenvector centrality (0.853)

Source article: U.S.China tariff truce sparks export rush amid shipping line cutbacks (2025-05-14)

Events:

1. Donald Trump won the U.S. presidential election in late 2024, creating tariff-related uncertainty that gripped global logistics.
2. Chinese exporters front-loaded cargo shipments to the U.S. around the turn of the year to clear inventories ahead of anticipated tariff hikes, driving the Shanghai Containerized Freight Index to 2,500 on January 3, 2025.
3. Donald Trump was inaugurated as U.S. President on January 20, 2025, and formally implemented tariffs on Chinese goods.
4. Shipping volumes on the U.S.-China route declined sharply after tariff implementation, with the contraction deepening by April 2025 as tit-for-tat duties reached 100 percent.
5. Major shipping lines curtailed services on the trans-Pacific route and reallocated container equipment to alternative hubs including Vietnam in response to slumping demand caused

by the protracted U.S.-China tariff war.

6. Blank sailings on Asia-North America routes spiked to 24 percent between late March and early May 2025, causing unshipped cargo to accumulate at major Chinese ports.
7. Freight rates dropped steeply, with the Shanghai Containerized Freight Index sinking to 1,345 as of May 9, 2025, representing a 42 percent decline from a year earlier.
8. Washington and Beijing enacted a 90-day tariff truce on May 12, 2025, temporarily suspending the trade conflict.
9. Chinese exporters began rushing to ship as much cargo as possible to the U.S. immediately after the May 12 truce announcement to maximize shipments before the grace period expires.

Predictions:

1. Competition for vessel space will intensify as exporters rush to ship cargo during the 90-

- day tariff truce window.
2. A bidding war for container slots could occur if the third-quarter peak shipping season coincides with front-loading during the tariff truce.
 3. Renewed freight rate volatility and potential bottlenecks at U.S. ports will emerge as the temporary ceasefire aligns with the industry's peak third-quarter shipping season.
 4. Cargo volume bound for the U.S. will experience a short-term spike as a result of the temporary ceasefire.
- story_11010 [central]: High eigenvector centrality (0.846)
- Source article:* China tariff pause lowers odds of empty U.S. shelves, but here's the catch for investors; Cargo shipping between China and the U.S. could see a double front-loading period this year as companies rush to exploit a temporary 90-day pause in trade hostilities (2025-05-12)
- Events:*
1. President Donald Trump imposed 'reciprocal' tariffs on April 2, 2025, causing levies on Chinese goods to surge to 145% and China to retaliate with 125% tariffs on U.S. products, threatening a trade embargo between the trade partners.
 2. Companies front-loaded goods in the first quarter of 2025, causing sharp increases in shipping activity between China and the U.S.
 3. The number of cargo ships headed to the U.S. from China surged in March 2025, then plunged to about 41 vessels around April 26, 2025.
 4. China exempted some goods from its U.S. tariff rate in late April 2025, and the U.S. gave a reprieve to smartphones and other consumer electronics from China, causing shipping volumes to begin climbing.
 5. The Trump administration agreed to lower its tariff rate to 30% on goods from China, and Beijing slashed its rate on American imports to 10%, creating a temporary 90-day pause in trade hostilities.
 6. The U.S. stock market surged on Monday, May 12, 2025, with the S&P 500 index rising 3.3%, the Dow surging 2.8%, and the Nasdaq Composite up 4.4%, exiting a bear market, while safe-haven assets like gold slumped.
 7. The number of cargo ships headed to the U.S. from China picked up to about 51 vessels by Monday, May 12, 2025.
 8. Treasury Secretary Scott Bessent stated at a press conference in Geneva on Monday, May 12, 2025, that neither side wants a decoupling of their relationship, while suggesting 30% was 'a floor' on China tariffs.
- Predictions:*
1. Companies will rush to front-load goods again during the 90-day pause, creating a second burst of shipping activity this year as they take advantage of the temporary tariff reprieve before the pause expires on August 10, 2025.
 2. California's ports will see a burst of fresh activity and potentially an earlier-than-usual peak shipping season this year as pent-up demand floods back into the market.
 3. The rebound in Chinese imports will reduce the risks of a supply-chain disruption, particularly in the run up to back-to-school and holiday sales later in 2025.
 4. The 90-day pause adds to more favorable odds of a permanent de-escalation being reached in 2025.
- story_11536 [coverage] (centrality 0.9597): Covers 77.8% of community (274/352 nodes)

Same story as above; its sequence is listed at its first appearance.

Narrative 12. Copper Tariff Shock and Market Price Volatility

Community id 11; size 305 stories.

Metric	Value
Nodes	305
Edges	9,481
Density	0.2045
Average degree	62.170
Average similarity	3.0342
Min similarity	1.2800
Max similarity	25.279
Clustering coefficient	0.6783

Characterization. This community centers on Trump’s sudden July 2025 announcement of a 50% copper tariff, creating unprecedented market volatility with Comex futures spiking 17% while London and Shanghai prices fell. It uniquely captures the dramatic price divergence between U.S. and global copper markets and the implications for AI infrastructure development dependent on copper-intensive data centers.

Key events.

- US President Donald Trump announced a 50 percent tariff on copper imports on Tuesday, July 8, 2025, stunning global markets and creating a watershed moment for the copper market.
- New York-listed copper futures spiked as much as 17 percent immediately after Trump’s announcement on Tuesday, July 8, 2025, as traders scrambled to lock in prices ahead of the anticipated tariff implementation.
- London and Shanghai copper futures declined more than 1 percent on Tuesday, July 8, 2025, reflecting market expectations of reduced US demand due to the tariff announcement.
- The price spread between Comex and LME copper futures for October delivery skyrocketed to almost US\$3,000 per tonne after Trump’s announcement.
- Late Wednesday, July 9, 2025, Trump announced that the copper tariff would take effect on August 1.

Key predictions.

- US officials will officially confirm the 50 percent tariff rate within weeks, and implementation will occur within 30 days according to Citi Research expectations.

- US copper prices will remain elevated as future supply risks grow if tariffs come in sooner than expected or at a higher level with no country exemptions.
- Copper cargoes previously destined for the US will be redirected to China or Japan once the tariff is realized.
- Copper prices will remain elevated this quarter (Q3 2025), then pull back in Q4 2025 and Q1 2026 if tariffs are implemented in the near term and the market gains clarity.
- The 50% copper tariff will considerably challenge the economics for all domestic data-center development currently being evaluated or underwritten.

Representative stories.

- story_5140 [central]: High eigenvector centrality (1.000)

Source article: Trump's 50% tariff shocker stokes copper market mayhem (2025-07-09)

Events:

1. US President Donald Trump announced a 50 percent tariff on copper imports on Tuesday, July 8, 2025, stunning global markets and creating a watershed moment for the copper market.
2. New York-listed copper futures spiked as much as 17 percent immediately after Trump's announcement on Tuesday, July 8, 2025, as traders scrambled to lock in prices ahead of the anticipated tariff implementation.
3. London and Shanghai copper futures declined more than 1 percent on Tuesday, July 8, 2025, reflecting market expectations of reduced US demand due to the tariff announcement.
4. The surge in US copper prices proved short-lived following the initial spike on Tuesday, July 8, 2025, due to lack of clarity on implementation details and timing.
5. The price spread between Comex and LME copper futures for October delivery skyrocketed to almost US\$3,000 per tonne after Trump's announcement, though analysts noted this did not fully price in the 50 percent tariff.
2. The tariff could come into effect much later than official hints suggest, given copper's critical importance to the US economy.
3. US copper prices will remain elevated as future supply risks grow if tariffs come in sooner than expected or at a higher level with no country exemptions.
4. The tariff implementation will abruptly close the window for further significant US-bound copper shipments, possibly for the rest of 2025.
5. Chile will make a strong and emphatic argument to get the tariff rate lowered, especially given Chile runs a trade deficit with the US.
6. Spot demand for copper shipments from Chile and Peru to the US Gulf Coast will remain supported in the near term, but volumes will taper off after tariff enforcement.
7. Copper cargoes previously destined for the US will be redirected to China or Japan once the tariff is realized.
8. The arbitrage window will likely close once the tariff implementation timeline is clear, and market stability and lower prices should gradually return.
9. Copper prices will remain elevated this quarter (Q3 2025), then pull back in Q4 2025 and Q1 2026 if tariffs are implemented in the near term and the market gains clarity.

Predictions:

1. US officials will officially confirm the 50 percent tariff rate within weeks, and implementation will occur within 30 days according to Citi Research expectations.
10. US copper premiums will ease from current highs but remain above historical norms relative to the LME.

- story_4105 [central]: High eigenvector centrality (0.976)

Source article: Trump's 50% tariff shocker stokes copper market mayhem (2025-07-10)

Events:

1. US President Donald Trump announced a 50 per cent tariff on copper imports on Tuesday, July 8, 2025, stunning global markets and creating a watershed moment for the copper market.
2. New York-listed copper futures spiked as much as 17 per cent immediately after Trump's announcement on July 8, 2025, as traders scrambled to lock in prices ahead of the anticipated tariff.
3. London and Shanghai copper futures declined more than 1 per cent on July 8, 2025, reflecting expectations of reduced US demand due to the tariff announcement.
4. The surge in US copper prices reversed quickly after July 8, 2025, due to lack of clarity on how and when the tariff would be implemented.
5. The price spread between Comex and LME copper futures for October delivery skyrocketed to almost US\$3,000 per tonne after Trump's announcement, though this did not fully price in the 50 per cent tariff.
2. US officials will implement the copper tariff in late July or early August 2025.
3. US copper prices will remain elevated as future supply risks grow if tariffs come in sooner than expected or at a higher level with no country exemptions.
4. Chile will make a strong argument to get the tariff rate lowered.
5. Spot demand for copper shipments from Chile and Peru to the US Gulf Coast will remain supported in the near term, but volumes will taper off after tariff enforcement.
6. Copper cargoes originally destined for the US will be redirected to China or Japan once the tariff is realized.
7. The pace of copper deliveries into the CME will pick up as traders who held back deliveries now release them.
8. The arbitrage window will close once the tariff implementation timeline is clear, and market stability and lower prices should gradually return.
9. Copper prices will remain elevated this quarter (Q3 2025), then pull back in Q4 2025 and Q1 2026 if tariffs get implemented in the near term and the market gains clarity.

Predictions:

1. Citi Research expects the US government to officially confirm the 50 per cent tariff rate within weeks and implement it within 30 days of confirmation.
10. US copper premiums will ease from current highs but remain above historical norms relative to the LME.

- story_20740 [central]: High eigenvector centrality (0.921)

Source article: How Trump's threat of 50% tariffs on copper could hurt America's AI ambitions; Copper futures ease back after ending at a record high Tuesday (2025-07-09)

Events:

1. On February 25, Trump directed Commerce Secretary Howard Lutnick to investigate whether copper imports pose a national security threat and to recommend mitigation measures including potential tariffs, export controls, or incentives for domestic production, giving Lutnick up to 270 days to report findings.
2. In March, the Copper Development Association responded to the investigation by stating that the U.S. copper semi-fabrication industry relies on imports from trading partners and warning that tariffs on refined copper cathodes would harm the domestic industry and potentially exacerbate national security risks.
3. In May, UBS estimated that global AI capital expenditures could grow by 60% in 2025 to \$360 billion and by another 33% in 2026 to \$480 billion.
4. On Tuesday, July 8, 2025, during a cabinet meeting, Trump announced his plan to impose a 50% tariff on copper imports, stating 'Today, we're doing copper. I believe the tariff on copper, we're going to make it 50%.'
5. On Tuesday, July 8, 2025, following Trump's tariff announcement, Comex copper September futures climbed 13.1% to settle at \$5.6855 a pound, an all-time high for the most-active

contract based on data going back to 1968 and marking the largest daily increase on record.

6. On Tuesday, July 8, 2025, U.S. Commerce Secretary Howard Lutnick stated in a CNBC interview that the duty likely will be put in place at 'the end of July, maybe Aug. 1' and that Trump will sign a proclamation within a day or two days.
7. Late Wednesday, July 9, 2025, Trump announced that the copper tariff would take effect on August 1.
8. On Wednesday, July 9, 2025, copper prices pulled back on Comex, ending 3.5% lower at \$5.49 a pound.

Predictions:

1. The 50% copper tariff will considerably challenge the economics for all domestic data-center development currently being evalu-

ated or underwritten

2. The tariffs will cause a sharp increase in U.S. copper prices, immediately raising costs for businesses building and expanding AI infrastructure
3. Tariff uncertainty will delay investment in AI, with the sudden price spike and supply constraints potentially delaying or derailing planned investments by major tech companies
4. Rising copper prices will significantly affect copper-intensive sectors such as building construction, equipment manufacturing, electric vehicles, and electronic products, and may fuel inflation concerns
5. The copper tariff will increase the cost and slow the pace of grid expansion and new energy integration, which are vital to supporting AI

• story_9597 [central]: High eigenvector centrality (0.903)

Source article: How Trump's threat of 50% tariffs on copper could hurt America's AI ambitions; Copper futures ease back after ending at a record high Tuesday (2025-07-09)

Events:

1. On February 25, Trump directed Commerce Secretary Howard Lutnick to investigate whether copper imports pose a national security threat and to recommend mitigation measures including potential tariffs, export controls, or incentives for domestic production, giving Lutnick up to 270 days to report findings.
2. In March, the Copper Development Association responded to the investigation by stating that the U.S. copper industry relies on imports from trading partners and warning that tariffs on refined copper cathodes would harm the domestic semi-fabrication industry and potentially exacerbate national security risks.
3. In May, UBS estimated that global AI capital expenditures could grow by 60% in 2025 to \$360 billion and by another 33% in 2026 to \$480 billion.
4. On Tuesday, July 8, 2025, during a cabinet meeting, Trump announced to reporters his plan to impose a 50% tariff on copper imports, stating 'Today, we're doing copper. I believe the tariff on copper, we're going to make it 50%.'
5. On Tuesday, July 8, 2025, following Trump's

tariff threat, Comex copper September futures climbed 13.1% to settle at \$5.6855 a pound, reaching an all-time high for the most-active contract based on data going back to 1968 and marking the largest daily increase on record.

6. On Tuesday, July 8, 2025, Commerce Secretary Howard Lutnick stated in a CNBC interview that the duty likely will be put in place at the end of July, maybe August 1, and that Trump will sign a proclamation within a day or two days after the ordinary legal process.
7. Late Wednesday, July 9, 2025, Trump announced that the copper tariff would take effect on August 1.
8. On Wednesday, July 9, 2025, copper prices on Comex pulled back, ending 3.5% lower at \$5.49 a pound.

Predictions:

1. The 50% copper tariff will considerably challenge the economics for all domestic data-center development that is currently being evaluated or underwritten
2. The tariffs will cause a sharp increase in U.S. copper prices, immediately raising costs for businesses building and expanding AI infrastructure
3. The sudden price spike and supply con-

straints could delay or derail planned investments by major tech companies in AI

4. Rising copper prices could significantly affect copper-intensive sectors such as building construction, equipment manufacturing, electric vehicles, and electronic products, and

might also fuel inflation concerns

5. A copper tariff could increase the cost and slow the pace of grid expansion and new energy integration, which are vital to supporting AI

- **story_8770 [central]: High eigenvector centrality (0.808)**

Source article: Trump sends copper prices crashing after his tariff exemption wrecked this popular trade; Comex copper prices drop by more than 20% Thursday (2025-07-31)

Events:

1. In January 2025, President Trump first mentioned imposing a tariff on copper imports, which unleashed record shipments of the metal to American ports as traders anticipated the tariffs.
2. From January to May 2025, traders executed an arbitrage strategy by buying cheaper copper on the London Metal Exchange and selling it at higher prices on the Comex in the U.S., causing copper to be rerouted to the U.S. and U.S. inventories to reach their highest levels in 21 years while LME inventories fell by about 50%.
3. In February 2025, President Trump ordered the start of a U.S. investigation into the potential threat that copper imports pose to national security.
4. On July 8, 2025, President Trump announced he planned to place a 50% tariff on copper imports, causing copper prices to spike 13% that day to a record-high finish of \$5.6855 a

pound.

5. On July 23, 2025, copper prices reached a fresh record high at \$5.82 per pound.
6. On Wednesday, July 30, 2025, the White House released details revealing that Trump would impose universal 50% tariffs on imports of semifinished copper products starting August 1, but would exempt copper input materials such as cathodes, anodes, and copper scrap from these tariffs.
7. On Thursday, July 31, 2025, Comex copper prices suffered the biggest one-day plunge on record, losing nearly 22.1% to end at \$4.3545 a pound, as the arbitrage trade collapsed following the tariff exemption announcement.

Predictions:

1. The copper market will shift focus to global fundamentals, with the market in supply surplus and delayed recovery in cyclical demand, slower growth expected in China in the second half of the year, and the European economy struggling.

- **story_9571 [coverage] (centrality 0.7813): Covers 62.6% of community (191/305 nodes)**

Source article: Market Talk Roundup: Latest on U.S. Politics (2025-07-10)

Events:

1. President Trump announces a 50% tariff on imports from Brazil, set to come into effect on August 1, 2025, citing legal action against Brazil's former President Jair Bolsonaro and U.S. tech firms as justification, making it the steepest tariff announced this week.
2. President Lula vows to reciprocate if Trump follows through with the Brazil tariff, raising the risk of a trade war.
3. President Trump announces a 50% tariff on global imports of copper, set to come into effect on August 1, 2025.
4. The Federal Reserve releases minutes from

its June policy meeting revealing officials are split over the outlook for interest rates.

5. China's strategic petroleum reserves absorb nearly all of the second-quarter oil surplus during the second quarter of 2025, tightening global supply.
6. Arabica coffee prices rise 0.4% to \$2.85 a pound in midday trade on July 10, 2025, after Trump's Brazil tariff announcement.
7. The Brazilian real stays under pressure and the dollar rises 0.1% to 5.5826 real on July 10, 2025, after Trump's tariff announcement.
8. London-listed miners push the FTSE 100 index to an all-time high of 8972.3 points on July 10, 2025, with Anglo American up 5.4%,

Rio Tinto and Glencore up above 4.5%, and Antofagasta up 2.9%.

9. U.S. copper prices hit record levels on July 10, 2025, following Trump's copper tariff announcement.
10. The iTraxx Europe Crossover index falls 1 basis point to 277bps on July 10, 2025, the lowest level in over 9 months.
11. Gold futures rise 0.2% to \$3,329.50 a troy ounce on July 10, 2025, supported by a softer U.S. dollar after Trump's tariff announcements.

Predictions:

1. U.S. import demand for coffee from Brazil will suffer unless exemptions are announced for products that cannot easily be grown in the U.S.
2. A trade war between the U.S. and Brazil

could disrupt coffee supplies.

3. The Brazilian real is likely to continue to trade on a softer footing in the near-term without a clear path to de-escalation.
4. The flow of copper into the U.S. will strengthen in the coming weeks as a result of tariffs, potentially tightening the market in Europe and China and putting upward pressure on prices.
5. If inflation data continues to cool, the likelihood of a Fed rate cut in September will become clearer, potentially weighing on the dollar and paving the way for further gold upside.
6. Fresh tariffs are expected to drive inflationary pressures through higher import costs.
7. OPEC+ banks on strong summer demand to absorb additional oil supply, but concerns over a potential glut later in 2025 persist.

- story_18119 [coverage] (centrality 0.2309): Covers 30.5% of community (93/305 nodes)

Source article: Gold price hits new peak logging 6.50% weekly gain on escalating US-China trade war, weak US dollar, Fed rate cut buzz (2025-04-12)

Events:

1. Donald Trump imposed hefty tariffs on trading partners including China, causing broad market disruption
2. The US unexpectedly paused tariffs on most trading partners except China, escalating US-China trade war tensions
3. China retaliated by increasing tariffs on US goods from 84% to 125%
4. The US dollar index fell below 100 to around 99.01, reaching a multi-year low
5. US consumer prices rose less than anticipated in March, both annually and month-

on-month

6. Gold prices climbed to new peaks with MCX gold hitting Rs.93,940 per 10 gm and spot gold touching \$3,245 per ounce on Friday

Predictions:

1. The US Federal Reserve may have increased scope for rate cuts this year
2. Spot gold price may soon touch \$3,280 and \$3,320 per ounce
3. MCX gold rate may soon touch Rs.95,000 to Rs.95,500 per 10 gm in the near term
4. Gold may reach Rs.100,000 per 10 gm in the long term

Narrative 13. Constitutional Challenge to Presidential Tariff Authority

Community id 12; size 244 stories.

Metric	Value
Nodes	244
Edges	19,746
Density	0.6661
Average degree	161.85
Average similarity	3.6891
Min similarity	1.2800
Max similarity	22.342
Clustering coefficient	0.8770

Characterization. This community focuses on the legal battle over Trump’s use of emergency powers to impose tariffs, culminating in the May 28, 2025 Court of International Trade ruling that invalidated reciprocal tariffs as unconstitutional. It distinctively addresses the separation of powers question and the judicial challenge to executive tariff authority under IEEPA.

Key events.

- On April 2, 2025, President Trump announced reciprocal tariffs of up to 25 percent on goods from 57 countries, including Korea, by invoking the International Emergency Economic Powers Act (IEEPA) and declaring the U.S. trade deficit a national emergency.
- In April 2025, a New York-based wine importer, four small- and medium-sized enterprises, and 12 U.S. state governments including Oregon and New York filed a lawsuit against the Trump administration’s reciprocal tariffs in the U.S. Court of International Trade.
- On May 28, 2025 (Wednesday), the U.S. Court of International Trade invalidated Trump’s reciprocal tariffs through a unanimous three-judge panel ruling because the U.S. Constitution grants taxing authority exclusively to Congress.
- After the May 28 ruling, the U.S. Court of International Trade ordered the Trump administration to issue a new executive order within 10 days to cancel the 10 percent baseline duty and block the delayed country-specific tariffs scheduled for July 8.
- The U.S. Court of Appeals for the Federal Circuit paused the lower-court order on May 29, 2025 so tariffs remain in effect while the case is litigated.

Key predictions.

- The U.S. Court of Appeals for the Federal Circuit will hear the Trump administration's appeal, and the U.S. Supreme Court will likely deliver a final decision on the reciprocal tariffs ruling within one to two months.
- Seoul will have more time to assess its negotiating strategy with the United States because the July 8 deadline for reciprocal tariff talks becomes irrelevant following the court ruling.
- The Trump administration will fight the tariff case all the way to the Supreme Court.
- The Supreme Court will resolve the tariff dispute.
- Legal challenges targeting the use of Section 232 and other authorities for the remaining product-specific tariffs (autos, steel, aluminum) could emerge.

Representative stories.

- story_15002 [central]: High eigenvector centrality (1.000)

Source article: Seoul prepares calm response after U.S. court blocks Trump's reciprocal tariffs (2025-05-29)

Events:

1. On April 2, 2025, President Trump announced reciprocal tariffs of up to 25 percent on goods from 57 countries, including Korea, by invoking the International Emergency Economic Powers Act (IEEPA) and declaring the U.S. trade deficit a national emergency to regulate international economic transactions.
2. On April 5, 2025, the Trump administration implemented a baseline 10 percent tariff on all imports as part of the reciprocal tariff policy announced on April 2.
3. In April 2025, a New York-based wine importer, four small- and medium-sized enterprises, and 12 U.S. state governments including Oregon and New York filed a lawsuit against the Trump administration's reciprocal tariffs in the U.S. Court of International Trade to challenge the legality of the tariffs.
4. On May 28, 2025 (Wednesday), the U.S. Court of International Trade invalidated Trump's reciprocal tariffs through a unanimous three-judge panel ruling because the U.S. Constitution grants taxing authority exclusively to Congress, which a president's emergency

powers cannot override.

5. After the May 28 ruling, the U.S. Court of International Trade ordered the Trump administration to issue a new executive order within 10 days to cancel the 10 percent baseline duty and block the delayed country-specific tariffs scheduled for July 8.
6. After the court ruling, the Trump administration's legal counsel filed an appeal to the U.S. Court of Appeals for the Federal Circuit and is considering an emergency motion to stay the ruling to reverse the decision blocking reciprocal tariffs.

Predictions:

1. The U.S. Court of Appeals for the Federal Circuit will hear the Trump administration's appeal, and the U.S. Supreme Court will likely deliver a final decision on the reciprocal tariffs ruling within one to two months.
2. Seoul will have more time to assess its negotiating strategy with the United States because the July 8 deadline for reciprocal tariff talks becomes irrelevant following the court ruling.
3. Legal challenges targeting the use of Sec-

tion 232 and other authorities for the remaining product-specific tariffs (autos, steel, alu-

minum) could emerge.

- **story_10392 [central]: High eigenvector centrality (0.961)**

Source article: Import taxes down, markets up: World waits for Trump reaction to courts blocking tariffs (2025-05-29)

Events:

1. Trump imposed tariffs on imports citing emergency authority under IEEPA on April 2, 2025
2. Trump paused most tariffs for 90 days after an uproar to negotiate trade deals
3. Trump imposed 145% tariffs on China, nearly halting trade between the countries
4. Trump and China reached an agreement on May 12, 2025 to lower tariffs to 30% while negotiations continue
5. The Court of International Trade ruled on May 28, 2025 that Trump lacked authority under IEEPA to impose the tariffs
6. U.S. District Judge Rudolph Contreras blocked the Trump administration on May 29, 2025 from collecting tariffs from two Illinois toy importers
7. Government lawyers appealed the trade-court ruling to the U.S. Court of Appeals for the Federal Circuit
8. The U.S. Court of Appeals for the Federal Circuit paused the lower-court order on May 29, 2025 so tariffs remain in effect while the case is litigated
9. Wall Street stock index futures rose by more than 1.5% before trading began on May 29, 2025 in response to the court ruling
10. White House Press Secretary Karoline Leavitt stated on May 29, 2025 that the administration expects the Supreme Court to resolve the issue
11. Trump spoke with Japan's Prime Minister Shigeru Ishiba on May 29, 2025 about trade
12. Canadian Prime Minister Mark Carney told the House of Commons on May 29, 2025 that the ruling is consistent with Canada's position that the tariffs were unlawful

Predictions:

1. The Trump administration will fight the tariff case all the way to the Supreme Court
2. The Supreme Court will resolve the tariff dispute
3. Three trade deals will be completed soon
4. The Trump administration will explore other options for imposing tariffs while continuing to pursue appeals

- **story_3820 [central]: High eigenvector centrality (0.953)**

Source article: Court overturns Trump's sweeping import tariffs (2025-05-29)

Events:

1. In early April 2025, Trump announced reciprocal tariffs on US trading partners, imposing a 20 percent tariff on EU products and higher tariffs on some countries, invoking the National Emergencies Act of 1977 based on the US's large trade deficit.
2. A few days after the initial tariff announcement in early April 2025, Trump froze tariffs for most countries at 10 percent for 90 days to negotiate separate trade agreements, but raised tariffs on China to over 100 percent.
3. Trump's tariff announcements caused a stock market crash in early April 2025 as markets reacted negatively to the size of the tariffs.
4. A group of companies and a group of states appealed Trump's tariff actions to the Federal Court of International Trade, claiming Trump violated Congress's power of the purse.
5. On May 29, 2025, the Federal Court of International Trade ordered the majority of Trump's import tariffs to be overturned, ruling that the National Emergencies Act does not give the president unlimited authority to impose tariffs on almost all countries.
6. The White House responded strongly to the court ruling on May 29, 2025, with Stephen Miller calling it a 'judicial coup,' and the US Department of Justice appealed the order.
7. Markets reacted cautiously positively to the court's decision on May 29, 2025, explaining caution by anticipating more twists in the tariff disputes.
8. Last week before May 29, 2025, Trump threat-

ened the EU with 50 percent import tariffs starting in June, but on Sunday before May 29, 2025, Trump confirmed the EU's steep tariffs would remain on hold until July 9, 2025.

Predictions:

1. The case will likely end up in the Supreme

Court

2. The White House expects the court's decision to be overturned in the next court of appeals
3. The EU will introduce retaliatory tariffs of 95 billion euros against the United States if necessary

- story_10377 [central]: High eigenvector centrality (0.947)

Source article: Trade Court Strikes Down Trump's Global Tariffs; Businesses and states had sued the government, saying the president didn't have the authority to impose the levies (2025-05-29)

Events:

1. President Trump imposed sweeping tariffs on virtually every nation in early April 2025 using the International Emergency Economic Powers Act of 1977, citing the U.S. trade deficit as a national emergency that posed an unusual and extraordinary threat to the economy.
2. Trump later paused the reciprocal tariffs for 90 days to allow for negotiations with trading partners.
3. New York-based wine importer V.O.S. Selections and four other small businesses sued the government in the Court of International Trade, challenging Trump's authority to impose the tariffs.
4. Oregon, New York and 10 other states sued the government in the Court of International Trade, challenging both the reciprocal tariffs and tariffs Trump imposed on Canada and Mexico over fentanyl smuggling and illegal immigration.
5. The Court of International Trade held hear-

ings on the cases, during which a three-judge panel questioned whether Trump had the authority under IEEPA to impose tariffs and whether a true national emergency existed.

6. On Wednesday, May 28, 2025, the Court of International Trade ruled that President Trump didn't have the authority to impose the sweeping tariffs under IEEPA and voided the levies.
7. Shortly after the Court of International Trade handed down its decision, lawyers for the Trump administration notified the court they will appeal the ruling.

Predictions:

1. Appeals from the Court of International Trade will be heard by the U.S. Court of Appeals for the Federal Circuit and ultimately the Supreme Court.
2. If the ruling is upheld, the Trump administration must find another justification for its global tariffs, potentially using Section 301 of the Trade Act of 1974.

- story_10359 [central]: High eigenvector centrality (0.926)

Source article: President Trump Isn't a Tariff King (2025-05-30)

Events:

1. President Trump declared fentanyl a national emergency and imposed tariffs on Mexico, Canada, and China in February 2025 using the International Emergency Economic Powers Act (IEEPA).
2. President Trump declared the U.S. trade deficit a national emergency and imposed varying tariff rates on countries worldwide in April 2025 using IEEPA.
3. President Trump later reduced the April tariffs to 10% across the board for 90 days to allow time for trade deal negotiations.

4. Small businesses and several states challenged President Trump's use of IEEPA to impose tariffs in the case V.O.S. Selections v. U.S.
5. The U.S. Court of International Trade blocked President Trump's sweeping tariffs on Wednesday, May 28, 2025, ruling in a 52-page decision by a three-judge panel that the President exceeded his emergency powers and bypassed discrete tariff authorities delegated by Congress.
6. The U.S. Court of Appeals for the Federal Circuit stayed the trade court's ruling on Thursday, May 29, 2025, while it considers Presi-

- dent Trump's emergency appeal.
7. A separate federal judge also ruled the tariffs illegal under IEEPA around the same time as the Court of International Trade decision.

Predictions:

1. The Supreme Court will likely rule against President Trump's tariffs by invoking the major-questions precedent.
2. President Trump may use other laws to impose tariffs, particularly Section 338 of the 1930 Smoot-Hawley Act.

- story_14796 [coverage] (centrality 0.6293): Covers 93.4% of community (228/244 nodes)

Source article: Comment: Trump doubled his steel tariffs - because he could (2025-06-03)

Events:

1. In 2018, Trump imposed 25% tariffs on steel and aluminium imports to the US under national security grounds, causing steel prices to rise 10%, sector profits to increase by \$2.5 billion, capacity utilization to jump from 74% to 80%, and nearly 10,000 jobs to be added within the sector.
2. During the 2024 election campaign, Trump and Biden opposed Nippon Steel's proposed \$15 billion acquisition of US Steel to win steelworker votes in Pennsylvania.
3. Days before leaving office, Biden blocked the Nippon Steel acquisition of US Steel.
4. Last week (late May 2025), the US Court of International Trade struck down Trump's baseline and reciprocal tariffs, ruling their use of national emergency powers was unconstitutional.
5. On Friday (May 30, 2025), Trump doubled the tariffs on steel and aluminium imports to the US to 50% and extended them to downstream products containing the metals.
6. After the court ruling, negotiations with China stalled because trade partners lost incentive to make deals with Trump given his questionable ability to implement tariffs.
7. After winning the election, Trump changed his mind and decided to approve the Nippon Steel acquisition of US Steel with conditions including a golden share for govern-

ment veto, a US chief executive, and a majority of Americans on the board.

Predictions:

1. The 2018 tariffs cost US downstream steel-using industries about \$5.6 billion and about 75,000 jobs, with the impact being short-lived as the industry resumed its long-term decline.
2. The appeal process could end up before the US Supreme Court.
3. Trump might resort to more cumbersome and time-consuming legislative mechanisms to continue his trade wars.
4. Canada and the European Union will retaliate against the doubled steel and aluminium tariffs.
5. The 50% tariffs on steel and aluminium will increase investment in the sector and improve profitability, plant utilization rates, and employment numbers.
6. The 50% tariffs will have far more significant and damaging impact on steel and aluminium users and US companies and consumers than the 2018 tariffs.
7. The economic benefits of the metals tariffs will be far outweighed by their costs to the rest of the US economy.
8. If Trump continues his trade wars, they will inflict broader damage on the world's largest economy.

Narrative 14. Rare Earth Magnet Export Ban and Manufacturing Standstill

Community id 13; size 231 stories.

Metric	Value
Nodes	231
Edges	9,547
Density	0.3594
Average degree	82.658
Average similarity	3.2197
Min similarity	1.2802
Max similarity	20.162
Clustering coefficient	0.7971

Characterization. This community documents China’s strategic retaliation through halting rare earth magnet exports in April 2025, creating an existential supply crisis for U.S. automakers and manufacturers. It uniquely highlights how a targeted export control on a single critical material could bring American automotive assembly plants to a complete standstill within weeks.

Key events.

- On April 4, 2025, the Chinese government abruptly halted exports of rare earth magnets to any country as part of its trade war with the United States.
- Two days after Trump imposed tariffs on April 2, China imposed export controls on some kinds of rare earths and heat-resistant magnets made from them in retaliation for U.S. tariffs.
- Last week before May 30, 2025, Ford Motor temporarily closed a factory in Chicago that makes Ford Explorer sport utility vehicles after one of its suppliers ran out of rare earth magnets.
- On Monday, May 26, 2025, China granted some export licenses for rare earth magnets to be shipped to the United States and Europe to partially ease supply chain disruptions.
- On May 19, 2025 (Monday before article publication), Chinese authorities granted export permits to at least six Chinese magnet firms, though with increased approval timelines.

Key predictions.

- American and European companies will run out of rare earth magnets in the coming days and weeks.
- American automakers will cut back production at factories across the Midwest and South in the coming days and weeks.
- China could bring America's automotive assembly plants to a standstill.
- Many more factories in the United States and Europe will have to close in the coming days and weeks if China does not resume full exports of rare earth metals.
- Small factories in South Carolina and Texas will start full production of rare earth magnets this year (2025).

Representative stories.

- story_10257 [central]: High eigenvector centrality (1.000)

Source article: U.S. Dependence on China for Rare Earth Magnets Is Causing Shortages (2025-06-02)

Events:

1. Two decades ago, factories in Indiana moved rare earth magnet production to China as demand for the magnets was starting to soar for cars, semiconductors, fighter jets, and robots.
2. On April 4, 2025, the Chinese government abruptly halted exports of rare earth magnets to any country as part of its trade war with the United States.
3. In mid-May 2025, the United States and China reached a trade truce, but China did not relax its restrictions on rare earth magnets as American officials had expected.
4. On Friday (May 30, 2025), President Trump suggested that China had continued to limit access to rare earth magnets.
5. In mid-April 2025, China's Ministry of Commerce gave a handful of export licenses to European companies after initially stopping all exports.
6. Last week (late May 2025), China's Ministry of Commerce gave a few more export licenses for American companies, but world supplies

are dwindling fast.

7. Some Chinese rare earth magnet makers stopped producing while waiting for permission to resume exports, creating a weeks-long gap in magnet production that is moving through supply chains.

Predictions:

1. American and European companies will run out of rare earth magnets in the coming days and weeks.
2. American automakers will cut back production at factories across the Midwest and South in the coming days and weeks.
3. The weekslong gap in magnet production will soon reach manufacturers.
4. China could bring America's automotive assembly plants to a standstill.
5. Small factories in South Carolina and Texas will start full production of rare earth magnets this year (2025).
6. President Trump and China's leader Xi Jinping could speak about trade as soon as this week (early June 2025).

- story_10353 [central]: High eigenvector centrality (0.993)

Source article: Export Controls Endanger a U.S.-China Truce (2025-05-30)

Events:

1. On April 2, 2025, President Trump imposed steep tariffs on imports from China and many other countries to protect American industries and address trade imbalances through unilateral trade policy measures.
2. Two days after Trump imposed tariffs on April 2, China imposed export controls on some kinds of rare earths and heat-resistant magnets made from them in retaliation for U.S. tariffs by implementing administrative trade countermeasures.
3. On May 12, 2025, the United States and China announced after weekend meetings in Geneva that they would suspend most of their recently imposed tariffs to de-escalate their trade confrontation through diplomatic negotiations.
4. On May 13, 2025, one day after the Geneva agreement, the U.S. Commerce Department banned Americans from using or financing Huawei artificial intelligence chips, contending the A.I. chips were based on prohibited export of American technology through regulatory enforcement.
5. In recent days after the Geneva agreement, President Trump suspended the sale

of some American semiconductor technology and aerospace equipment needed for China's commercial aircraft, the C919, to limit China's economic development and military capabilities through export control measures.

6. Last week before May 30, 2025, Ford Motor temporarily closed a factory in Chicago that makes Ford Explorer sport utility vehicles after one of its suppliers ran out of rare earth magnets due to China's export restrictions by halting production operations.
7. On Monday, May 26, 2025, China granted some export licenses for rare earth magnets to be shipped to the United States and Europe to partially ease supply chain disruptions through selective administrative approvals.

Predictions:

1. Many more factories in the United States and Europe will have to close in the coming days and weeks if China does not resume full exports of rare earth metals.
2. If China maintains export controls on rare earths, many multinational companies may conclude that their supply chains are too reliant on China and increase calls in Europe for de-risking from China.

- story_15303 [central]: High eigenvector centrality (0.957)

Source article: Rare earth exports surged before controls imposed (2025-05-22)

Events:

1. On April 2, 2025, US President Donald Trump announced 'reciprocal tariffs' against China.
2. On April 4, 2025, Beijing added seven rare earth elements to its export control list in response to Trump's tariff announcement.
3. In March 2025, overseas buyers stockpiled rare earth elements ahead of Beijing's export controls, driving export volume to a nine-month high of 5,600 tonnes, up 20.3% year on year.
4. In April 2025, China's rare earth exports decreased from March but still rose 4.8% year on year to 4,785 tonnes, while permanent magnet exports plummeted 45.1% year on year to 2,626.7 tonnes.
5. In early May 2025, Beijing pledged to crack down on critical minerals smuggling by in-

creasing controls on upstream sources and targeting transshipments.

6. Following the 90-day trade truce reached in Geneva, Beijing suspended non-tariff countermeasures imposed since April 2, 2025, but did not address rare earth export controls.
7. On May 19, 2025 (Monday before article publication), Chinese authorities granted export permits to at least six Chinese magnet firms, though with increased approval timelines.

Predictions:

1. China's rare earth dominance will continue for the foreseeable future as the West pursues alternatives.
2. The rare earth trade will be high on the agenda in further talks between Beijing and Washington.

- story_10217 [central]: High eigenvector centrality (0.954)

Source article: U.S. Bracing For Shortage In China Ore (2025-06-04)

Events:

1. Two years ago (approximately 2023), factories in Indiana moved rare earth magnet production to China as demand for magnets began soaring for cars, semiconductors, fighter jets, and robots.
2. On April 4, 2025, the Chinese government abruptly halted exports of rare earth magnets to any country as part of its trade war with the United States.
3. In mid-May 2025, the United States and China reached a trade truce, but China did not relax its restrictions on rare earth magnets as American officials had expected.
4. In mid-April 2025, China's Ministry of Commerce issued a handful of export licenses to European companies after requiring separate licenses for future shipments.
5. Last week (late May 2025), China's Ministry of Commerce issued a few more export licenses for American companies, but world supplies continued dwindling fast.

6. During the weeks following the export halt, some Chinese rare earth magnet makers stopped producing while waiting for permission to resume exports, creating a gap in production moving through supply chains.

Predictions:

1. American and European companies will run out of rare earth magnets in the coming days and weeks.
2. American automakers will cut back production at factories across the Midwest and South in the coming days and weeks.
3. The weekslong gap in Chinese magnet production will soon reach manufacturers as it moves through supply chains.
4. Small factories in South Carolina and Texas will start full production of rare earth magnets this year (2025).
5. President Trump and China's leader Xi Jinping could speak about trade as soon as this week (early June 2025).

- story_16354 [central]: High eigenvector centrality (0.904)

Source article: Rare earth leverage puts China at centre of global trade battle (2025-05-03)

Events:

1. In 2010, China banned rare earth exports to Japan during the Senkaku Islands dispute, demonstrating its willingness to leverage rare earth dominance as geopolitical capital.
2. In 2014, the World Trade Organization ruled against China for distorting global markets through export restrictions on rare earths.
3. In 2022, the US launched the CHIPS Act to curb China's access to advanced semiconductor technology.
4. Between 2023 and 2025, China imposed restrictions on exporting strategic materials including gallium, germanium, antimony, graphite, and tungsten to the US, and announced a ban on rare earth extraction and separation technologies.
5. In April 2025, the Trump administration im-

posed 145% tariffs on Chinese goods.

6. In April 2025, China's Ministry of Commerce placed export restrictions on seven medium and heavy rare earth elements and their derivative magnets in retaliation for US tariffs, requiring firms to apply for licenses to export and placing 16 American entities on its export control list.

Predictions:

1. Chinese export curbs may trigger a global scramble for alternative rare earth sources, creating opportunities for India and other countries to fill the market gap, though developing capabilities will take several years and face significant challenges.
2. The race to secure critical rare earth resources will shape the future of global trade and the balance of technological and strategic power in the years ahead.

- story_5764 [coverage] (centrality 0.5173): Covers 71.0% of community (164/231 nodes)

Source article: Tariffs ignore the reality of tech supply chains (2025-04-19)

Events:

1. Six months before April 2025, Nvidia epitomized what investors liked about the American economy with sky-high profits, impressive innovation, and charismatic founder Jensen Huang.
2. Trump imposed 145 percent tariffs on China, prompting Beijing to impose export controls over seven critical minerals this week in April 2025.
3. On Wednesday (April 16, 2025), Nvidia warned of a looming \$5.5 billion earnings hit from new US export restrictions on sales of its chips to China.
4. After Nvidia's warning, Huang dashed to China to salvage his deals while Congress unleashed a probe, causing Nvidia's stock price to tumble along with other tech companies.
5. In 2010, China imposed export controls on critical minerals against Japan amid a fight,

sparking Japan to create massive stockpiles and develop alternative sources over 15 years, cutting dependency from 90 percent to 58 percent.

Predictions:

1. America will be on the back foot for the foreseeable future regarding critical minerals supply due to lack of stockpiles and preparation.
2. The White House will seek alternative sources of critical minerals from the seabed or places such as Ukraine, but this will probably take a few years to materialize.
3. Trump may retreat from his tariff position because he is transactional rather than ideological.
4. Investors should brace for more tech supply shocks with Nvidia being just the leading edge in a potential storm.

C.2 Characterization Prompt

System prompt. You are an expert analyst of narratives and stories. Your task is to characterize multiple communities of related stories, giving each a **DISTINCTLY DIFFERENT** title and description that highlights what sets it apart from the others.

User prompt. I'm providing N communities of related news stories. For each one, produce:

1. A concise title (up to 10 words).
2. A 2–3 sentence characterization capturing the core narrative and what makes it distinctive.
3. Up to 5 key events quoted verbatim from the stories (one per line, prefixed with a dash). Events are realized or reported occurrences (what already happened), not forecasts.
4. Up to 5 key predictions quoted verbatim from the stories (one per line, prefixed with a dash). Predictions are forward-looking claims about what will happen. Do not repeat items listed as key events. If a community has no predictions, write “None”.

IMPORTANT: These communities all concern the same broad topic. You **MUST** give each a title and description that clearly differentiates it from the others in this set. Read all N communities before writing anything.

Respond using **EXACTLY** this format, repeating it for every community:

=== COMMUNITY #<idx> ===

1. [Title]
2. [Characterization]
3.
 - [key event]
 - [key event]
4.
 - [key prediction]
 - [key prediction]

Here are the N communities:

-- COMMUNITY #<idx> (Size: <num_nodes> stories, avg similarity: <avg_similarity>)
--

Central stories (most representative):

- Story 1:
 - <event>
 - <event>

- Story 2:
 - <event>

Coverage stories (for breadth):

- Story 1:
 - <event>
 - <event>

D Construction of Narrative Signals

D.1 Data: Building Measures of Tariff Exposure and the Price of Tariffs

D.1.1 Structural Industry-Level Tariff Exposure

I construct a measure of structural (statutory) tariff exposure of commodities in the US using the US tariff schedule, and trade and production data. Following [Fajgelbaum et al. \(2020\)](#) and [Amiti et al. \(2019\)](#) I define tariff exposure for good g on day t as the effective tariff rate weighted by the import penetration share:

$$\text{tariff exposure for good } g \text{ at time } t = \frac{\sum_c \text{tariff-rate for good } g \text{ imported from country } c \text{ in } t \times \text{imports of } g \text{ from } c \text{ in } t}{\text{US production of } g \text{ in } t - \text{US exports of } g \text{ in } t + \text{total imports of } g \text{ in } t}$$

where total imports is just the sum of country-specific imports across all countries which send good g to the US. The absorption rate (i.e., the denominator) accounts for the relative importance of foreign goods in US domestic markets.

All import, export, and production data is available only on the monthly level, while tariff rates vary within-month. Thus, daily within-month changes in tariff exposure are a function only of changes in trade policy. In the remainder of this subsection, I explain how the above measure is constructed in practice.

HTS Tariff Revisions: Tariff Rates I begin with the Harmonized Tariff Schedule provided by the United States International Trade Commission, which maintains comprehensive records of official tariff rates and statistical categories for all imports into the US. I extract all 12 HTS “Revisions” from 14 March 2025 (the last revision before the sample begins on 1 April 2025, to compute the pre-“Liberation-Day” base tariff rates) to 1 July 2025 (the last revision before the sample ends; the next revision was on 1 August 2025, while my sample ends of 31 July 2025):

Revision 5 (2025-03-14),
Revision 6 (2025-04-02),
Revision 7 (2025-04-05),
Revision 8 (2025-04-10),

Revision 9 (2025-04-10),¹⁰
Revision 10 (2025-04-14),
Revision 11 (2025-05-02),
Revision 12 (2025-05-13),

Revision 13 (2025-05-16),
Revision 14 (2025-06-02),
Revision 15 (2025-06-23),
Revision 15 (2025-07-01),

where Revision 6 corresponds exactly to Liberation Day.

From these regime changes, I construct $\text{tariff_rate}_{g,t,c}$ the daily effective tariff rate on imports into the US at the HTS10 product code $g \times \text{day } t \times \text{country-of-origin } c$

¹⁰Though they were issued on the same day, the 2025 HTS Revisions 8 and 9 were treated as distinct by in the USITC records; in practice, as my data varies on the the daily level, they collapse to a de facto single revision.

level.¹¹

Import and Export Data I obtain US import and export data, likewise at the HTS10 product level (and the export-specific HTS10-equivalent, called Schedule B 10-digit), from the USA Census Bureau’s international trade API.¹² The data is available only per month, and can be prorated to the business-day level via uniform smoothing; in practice, as all trade and production data is monthly, the smoothing is superfluous. I collect imports from the designation Imports for Consumption and exports from Domestic Exports to avoid the circular re-exporting patterns: that is, goods from abroad intended to be re-exported directly never enter the calculations as they never make it into US markets directly.

The import panel contains one observation per (HTS10, country-of-origin, year-month), covering 18,609 distinct HTS10 codes, 232 countries, and 6 months (March-August, 2025). US export statistics, meanwhile, use Schedule B codes, which share the same 6-digit HS heading as HTS import codes¹³ but diverge at the 8- and 10-digit level. Only 30% of HTS10 import codes have an exact Schedule B match; the remaining 70% require HS6-level proration, so I aggregate all export data to the HS6 level for consistency.

Production Data At the time of writing, production data was not available for March-July, 2025. In general, production data is also published at the more coarse NAICS6 (industry) level on a monthly basis,¹⁴ and the most recent year available is 2023. I extract this data from the Annual Integrated Economic Survey. For each NAICS6 code and each month, I take the 2023 monthly production data from the Census, and the quotient of IPI for the corresponding 2025 and 2023 months: the Industrial Production Index, provided by the Federal Reserve Economic Data (FRED), tracks changes in output produced. The approximation is, therefore:

$$\text{production}_{\text{NAICS6}(g),m,2025} = \text{production}_{\text{NAICS6}(g),m,2023} \times \frac{\text{IPI}_{\text{NAICS6}(g),m,2025}}{\text{IPI}_{\text{NAICS6}(g),m,2023}}$$

¹¹Some tariffs in the sample are assigned to all goods originating from a country c ; others are product-specific; others still are unique to a product-country combination. I construct a correspondence which accounts for all of these granularities and takes into account exceptions and special provisions. HTS10 product codes are the most granular identifiers of products available, and the level on which product-specific tariff laws are written.

¹²api.census.gov/data/timeseries/intltrade/imports/hs and api.census.gov/data/timeseries/intltrade/exports/hs, respectively

¹³HTS10 is just the international Harmonized System (HS) 6-digit code extended by four US-specific digits.

¹⁴Again, it’s possible to impute daily values via uniform proration over trading days.

IPI data is typically published by FRED at the slightly coarser NAICS4 or NAICS3 level; I employ a fallback algorithm to take the most granular IPI data available.

To match NAICS6-level production data with HTS10-level import and export data, I rely on the methodology proposed by [Pierce and Schott \(2012\)](#), who provide a concordance built from the Census Bureau’s monthly trade concordance files between the 10-digit HTS10 codes and 6-digit NAICS codes for 2017-vintage data. Because I use production data from the AIES 2023 survey, with 2022-vintage NAICS codes, I develop fallback rules to manually address codes untreated in older vintages. The concordance yields approximately 37,000 crosswalk pairs.

NAICS codes exist only for manufacturing. About 89.5% of HTS10 rows match directly with a manufacturing NAICS code. For the remaining 10.5%, following the convention of [Fajgelbaum et al. \(2020\)](#) and [Amiti et al. \(2019\)](#), when domestic production is unobservable or zero for a category, I resort to the simplifying assumption that production is equal to exports – that is, that import penetration is 1 – and so tariff exposure collapses to the effective tariff rate. This is the conservative lower bound, the default practice in the literature, and is quite reasonable given that the US is known to be highly import-dependent for the goods affected (crude petroleum, certain ores, and some agricultural commodities like coffee and bananas).

Product-day level tariff exposure Combining all of the above, I obtain:

$$\begin{aligned} \text{HTS_exp}_{g,t} &= \frac{\sum_c \text{tariff_exposure}_{g,t,c} \times \text{imports}_{g,m \mapsto t,c}}{\text{production}_{\text{industry}(g),m[2023 \mapsto 2025] \mapsto t} + \text{exports}_{\text{industry}(g),m \mapsto t,c} - \sum_c \text{imports}_{g,m \mapsto t,c}} \\ &= \frac{\sum_c \text{tariff_exposure}_{g,t,c} \times \text{imports}_{g,m,c}}{\text{production}_{\text{industry}(g),m[2023 \mapsto 2025]} + \text{exports}_{\text{industry}(g),m,c} - \sum_c \text{imports}_{g,m,c}} \end{aligned}$$

where any imputations or approximations and their sources are summarized with the $\mapsto$ symbol. Because all monthly-to-daily prorations would be obtained via uniform smoothing (i.e., dividing the relevant metric by the number of trading days), the operation is superfluous and would just result in an identical scaling of both the numerator and denominator, so it’s omitted.

This measure has two properties that make it useful for identification. First, it is external to the narrative analysis and objective: it is constructed entirely from the statutory tariff schedule and trade flow data, with no reference to stock prices, returns or narratives per se. Second, it is time-varying: $\text{HTS_exp}_{g,t}$ updates whenever the tariff schedule changes (executive orders, retaliatory measures, 90-day pauses), providing policy-driven variation within the sample.

Restricted to the window of trading days between 1 April 2025 and 31 July 2025,

the resulting panel contains 1,557,528 observations (18,542 HTS10 codes $\times$ 84 trading days, excluding codes with zero imports in all months). The HS6 panel contains 458,640 observations (5,460 HS6 codes $\times$ 84 trading days). To match tariff exposure to both stocks and commodities, I aggregate the measure to the level of HS6 codes (indeed, the HTS10 level is particular to the USITC). The overall effective tariff exposure on the market level is summarized by industry in Figure D.1.

D.1.2 Long–Short Portfolio and the Price of Tariffs

Portfolio construction On each trading day t , all 5,460 HS6 codes are ranked by their exposure. The *long leg* consists of the top 30% by exposure (codes most heavily taxed relative to their absorption); the *short leg* consists of the bottom 30%. The top/bottom-30% percentile thresholds are recomputed daily, so the composition of each leg shifts whenever a tariff revision alters the cross-sectional ranking. I restrict to commodities as the cleanest distillation and lowest-tier good in any supply chain. In keeping with the Fama and French (1992, 1993) style of long-short portfolio construction, each HS6 code in each portfolio leg is given the same weight.

Commodity price data For each of the 5,460 HS6 codes in the exposure panel, I source daily commodity spot prices from a variety of sources to obtain a price. Because many HS6 codes within a chapter share the same underlying price series (e.g. all flat-rolled steel products map to the HRC futures contract), the effective number of independent price signals per leg is smaller than the raw HS6 count. Proceeding in hierarchical fashion, I pair the HS6 codes with exchange-traded US spot prices or the appropriate de facto spot (as commodities are sometimes traded only through futures), sourced from Yahoo Finance and Bloomberg. I restrict the portfolio construction to commodities having US spots and futures. Commodities having foreign prices only are excluded for failing to address US market in particular; monthly data are excluded because they have no within-month variation; and ETFs are excluded because the index price is informed by too many macro parameters and fails to capture the tariff dimension as well as commodities do.¹⁵ Following Fama and French (1992, 1993) and Jegadeesh and Titman (1993), I maintain the ex-ante sorting rule and do not re-fill the portfolios after excluding commodities with unusable prices to avoid endogenous selection and contamination by “middle values.”

The long leg reliably features HRC steel (40 HS6 product codes), soybeans (28 HS6 codes), cotton (49 codes), wheat (22 codes), gold (27 codes) and copper (19 codes); while

¹⁵Missing data are then patched with monthly World Bank Pink Sheet prices and ETF proxies. It is important to note that many HS6 codes correspond to composite goods and are manufactured with more than one input, so it is natural that they will not be associated to a commodity price.

Daily Tariff Exposure -- Manufacturing (NAICS3) and Non-Manufacturing HS6 Categories
(independent y-axis per panel; dashed verticals = tariff revision dates; exposure = $\sum(\text{rate} \times \text{imports}) / \sum \text{absorption}$)

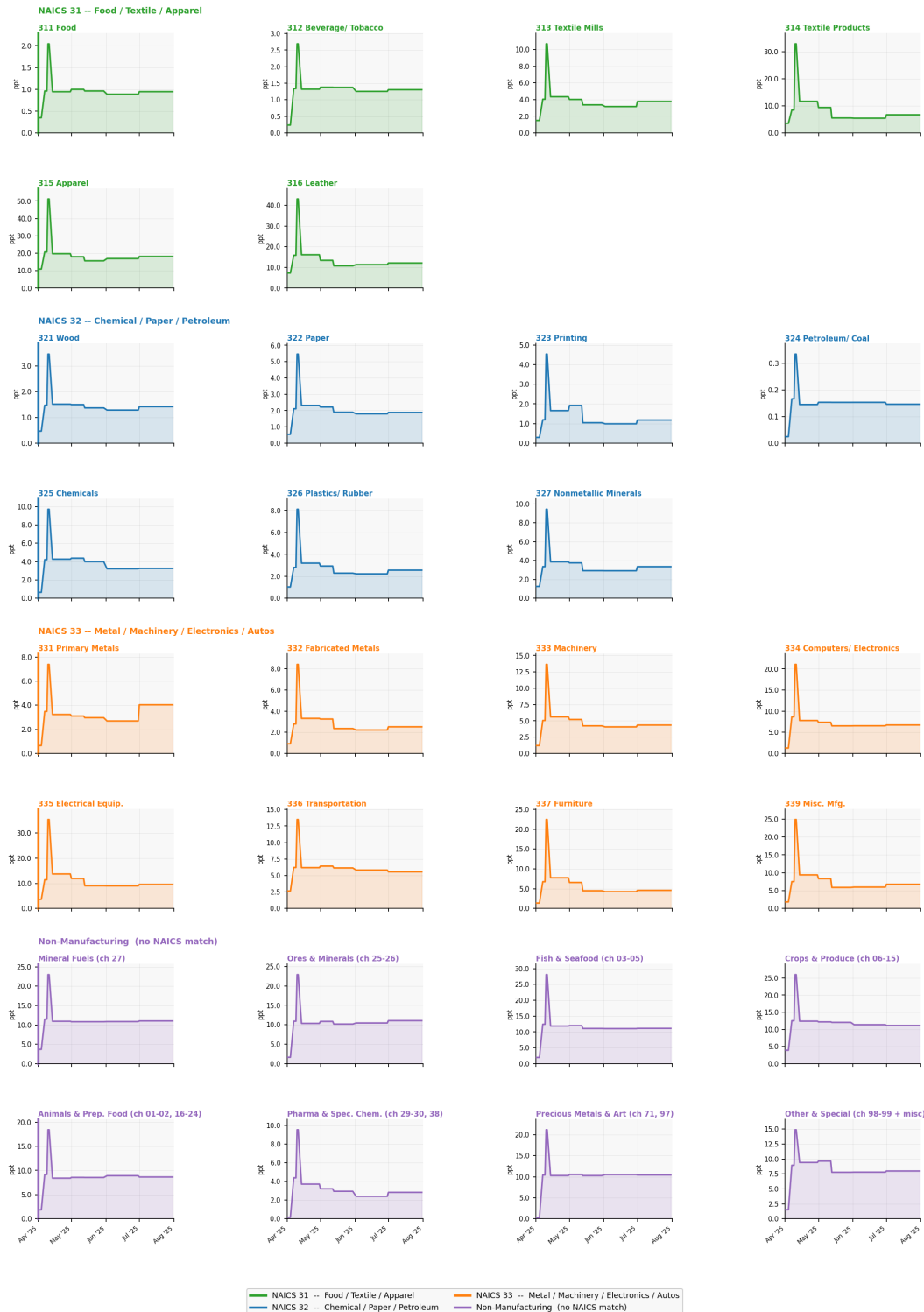


Figure D.1: Daily Tariff Exposure by Industry, March - August, 2025

Industry-level statutory exposure to tariffs, by NAICS codes (manufacturing) and HS6 product codes (non-manufacturing).

the short leg typically contains HRC steel (a wholly distinct set of 75 codes), cotton (again, a different set of 57 codes), soybean oil (24 codes), and soybean meal (12 codes). That steel and cotton make it into the different legs is to be expected: they span a huge variety of HS6 codes, which are exposed to very different tariff regimes, but nonetheless correspond to the same commodity market price. As the long-short portfolio is constructed with uniform weights, any such duplications cancel each other out – except if one portfolio leg has more HS6 codes. The resulting portfolios have an average of 25 (long) and 23 (short) unique commodities in each leg, and are very stable over time.

Factor return The simple daily return for commodity s is $\Delta p_{s,t} = (p_{s,t} - p_{s,t-1})/p_{s,t-1}$. The factor return on day t is the equally weighted long-leg average minus the equally-weighted short-leg average:

$$\Delta_t = \overline{\Delta p_t}^{\text{long}} - \overline{\Delta p_t}^{\text{short}}.$$

Figure D.2 summarizes the behaviour of the factor. The long and short legs meaningfully diverge as the tariff regime intensifies and, at its height, the factor accumulates an approximately 2% cumulative return over the window, consistent with high-tariff-exposure commodities bearing greater price pressure than lower-exposure ones.¹⁶ The exclusion of global prices, monthly data, and ETFs are corroborated by the fact that their inclusion completely closes the gap between the long and short branches of the constructed portfolio (a clear artifact of not having the right price data): this is an important validation exercise and confirms that the long-short portfolio does indeed isolate the direct effect of tariffs on US markets.

¹⁶By the end of the sample, as trade deals are signed, the cumulative return drops to near-zero levels.

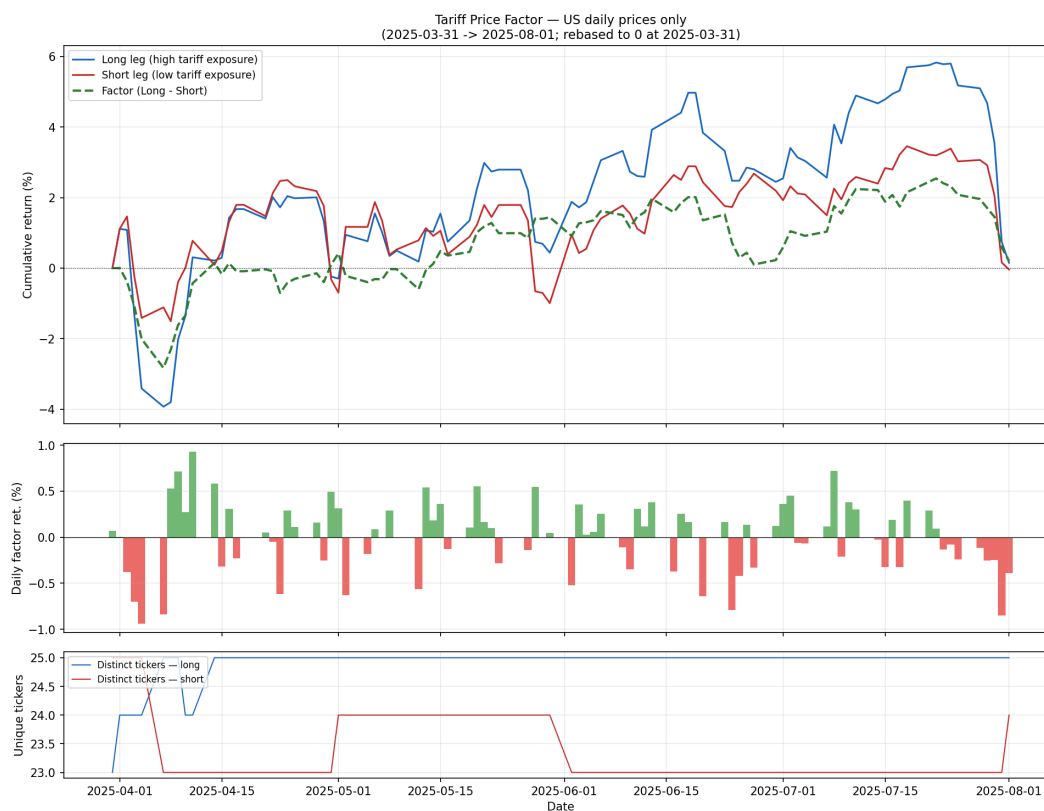


Figure D.2: Daily Tariff Exposure by Industry, March - August, 2025

The long leg is constructed from the top 30% of HS6 commodity codes ranked by tariff exposure; the short leg - from the bottom 30%. Prices are US exchange-traded futures and EIA spot prices only. Both legs are equally weighted across HS6 codes and rebased to zero on March 31, 2025. The factor return (dashed) is the daily long-minus-short spread. The middle panel shows daily factor returns; the bottom panel shows the number of distinct commodity price series in each leg (median: 25 long, 23 short). The factor accumulates approximately +2 percentage points at its height.

D.2 Fused Lasso Penalty λ Selection Criterion

The implementation of the fused LASSO relies on a choice of λ_{tv} . The model is used to construct a return decomposition of the tariff-price long-short commodity portfolio, not a forecast, so features are contemporaneous: $\mathbf{x}_t$ explains y_t on the same trading day. The decomposition exercise is consistent with market efficiency: information embedded in a given day's news coverage is priced into that day's return; there is no requirement that narratives at date t have any predictive power over financial activity at date $t + 1$. Any contemporaneous model evaluated on a predictive (out-of-sample) criterion will inevitably have a negative out-of-sample R^2 ; this is not evidence of model failure, and instead is suggestive of efficiency. As standard criteria for selecting regularization penalties – rolling OOS R^2 , masked-loss block cross-validation, AIC, BIC – are all designed to minimize future-oriented prediction error, they are fundamentally inappropriate tests. I therefore develop a narrative-decomposition-specific selection criterion that works directly on the full-sample solution and assesses the model's capacity to detect narrative regime changes in contemporaneous fashion.

For each candidate λ on a 10,000-point log-spaced grid on $[10^{-9}, 2.0]$, I define four statistics from the full-sample solution $\hat{\beta}(\lambda)$:

$$\begin{aligned} J(\lambda) &= \#\{(k, t) : |\hat{\beta}_{k,t}^{\text{std}} - \hat{\beta}_{k,t-1}^{\text{std}}| > \varepsilon\}, \\ \text{TV}(\lambda) &= \sum_k \sum_{t \geq 2} |\hat{\beta}_{k,t}^{\text{std}} - \hat{\beta}_{k,t-1}^{\text{std}}|, \\ S(\lambda) &= \frac{\text{TV}(\lambda)}{J(\lambda)} \\ V(\lambda) &= \frac{1}{(T-1)K} \sum_{k=1}^K \sum_{t=2}^T (\hat{\beta}_{k,t}^{\text{std}} - \hat{\beta}_{k,t-1}^{\text{std}})^2 \end{aligned}$$

where $\varepsilon = 10^{-5}$ separates genuine jumps from solver noise. $J(\lambda)$ counts active regime changes. $\text{TV}(\lambda)$ computes the sum of all absolute coefficient changes. $S(\lambda)$ is the *mean episode size*. V is the mean squared coefficient change and measures how “jagged” the fitted paths are. the average absolute magnitude of a surviving regime change.

I select

$$\lambda^* = \underset{\lambda}{\operatorname{argmax}} S(\lambda), \quad (4)$$

which maximizes the mean episode size.¹⁷

¹⁷The ℓ_1 TV penalty operates by progressively fusing small coefficient breaks as λ increases. At low λ , many small, noisy transitions survive and $S(\lambda)$ is low: total variation is spread thinly across many breaks. As λ rises, noise breaks are fused away but total variation is conserved and redistributed onto the breaks that survive. S rises. Eventually λ is large enough to collapse genuinely distinct narrative episodes into one another, and S falls. The interior maximum of S is the penalty at which the concen-

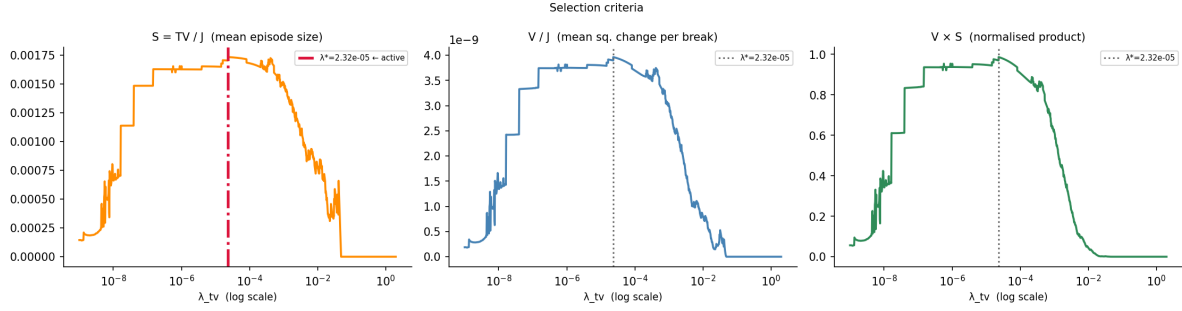


Figure D.3: Comparison of λ_{TV} selection criteria

Evaluation of parameters for choice of λ_{TV} penalty in fused LASSO: S, TV, V . All criteria evaluated on the same 10,000-point log-spaced grid. Optimal λ for each criterion (the points at which maxima are attained) are indicated in vertical lines.

I also consider alternative criteria: V/J , which optimizes the mean square change per regime break, and a normalized product $\frac{V}{\max(V)} \times \frac{S}{\max S}$ which allows for a natural trade-off between S and V . For this particular data, the optima are almost identical, further corroborating the choice.

An alternative design, cross-validation with random omitted single days, works as well and delivers qualitatively similar results, but lacks statistical power due to the sample size.

D.3 Robustness of the Fused LASSO

I perform three robustness exercises addressing orthogonal threats to the reliability of the narrative signals: the first confirms that the fused Lasso improves fit over a constant OLS model; the second tests the sensitivity of the narrative regime to the choice of λ_{TV} ; the third constructs confidence intervals around the estimated coefficient paths.

Comparing the fused Lasso to OLS coefficients. The OLS robustness check in Table D.1 compares the fused Lasso decomposition to a simpler benchmark in which each narrative has one constant coefficient over the full sample. In the corrected 84-trading-day sample, the constant-coefficient OLS model explains about 39% of tariff-factor return variation, while the fused Lasso fit substantially reduces the residual sum of squares almost by allowing narrative coefficients to change over time. Using the fused Lasso effective degrees of freedom, the approximate F-test rejects the null of time-constant coefficients

tration effect is maximal: all noise-driven micro-transitions have been eliminated while all well-separated narrative episodes survive intact. Breaks at λ^* are, on average, as large and as clean as they can be without over-aggregation. This is precisely the structure the research question demands: a small number of sharp, interpretable regime changes, free of noise.

($F(57, 11) = 23,312.89, p < 0.001$), indicating that the time-varying structure adds substantial explanatory power relative to OLS. This result should be interpreted as diagnostic evidence rather than a standalone proof of causal structure, because the selected fused Lasso remains highly flexible, with many effective breakpoints and limited residual degrees of freedom. More conservative robustness checks therefore focus on whether the same narrative episodes remain stable across penalty choices and bootstrap resampling.

Table D.1: Time-varying LASSO versus time-constant OLS benchmark

	Time-constant OLS	TV-LASSO
Observations	84	84
Narratives	15	15
λ_{TV}	–	2.324e-05
Residual sum of squares	7.618e-04	6.156e-09
R^2	0.3938	1.0000
Effective degrees of freedom	16	74
Active TV-LASSO breaks	–	58
<i>Approximate F-test for time-varying coefficients</i>		
F-statistic	21,336.64	
Numerator df	58	
Denominator df	10	
p-value	< 0.001	
ΔR^2	0.6062	

Notes: The OLS benchmark estimates one constant coefficient per narrative over the sample. The TV-LASSO allows piecewise-constant coefficients with an L1 total-variation penalty. The F-test is approximate and uses the fused-LASSO effective degrees of freedom $df_{TVL} = K_{\text{feat}} + J$.

Robustness to λ^* : a bootstrap window. I assess sensitivity of the estimated piece-wise constant coefficient paths to the strength of the fused Lasso penalty. That is, I check whether a slight departure from the optimal value λ_{tv}^* would have given vastly different coefficient paths. Using a circular block bootstrap on trading days with block length 8 (to preserve short-run dependence in returns and narratives) and $B = 100$ independent bootstrap draws, I repeatedly refit a purely TV-penalized specification on each resampled dataset; at each draw, I evaluate λ_{tv} on a log-spaced grid of 40 multipliers from 0.01 to 100 times λ_{tv}^* . For each (draw, λ) pair I compute $S(\lambda)$. Conceptually similar to the one-standard-error rule in cross-validated penalized regressions (Friedman et al., 2010), I retain all λ for which the bootstrap mean of $S(\lambda)$ lies within one bootstrap standard error of the mean at λ_{tv}^* ; the smallest and largest such λ on the grid yield lower and upper multipliers of λ_{tv}^* . I then refit the full fused Lasso specification on the complete calendar

sample for 81 log-spaced values of λ_{TV} between those bounds, widening the multiplier interval by a factor 1.5 relative to the bootstrap window for conservatism, and overlay the resulting day- t coefficient paths. In other words, I assess the coefficient path stability for paths obtained from λ_{TV} corresponding to $S(\lambda_{TV})$ within 1.5 standard deviations of $S(\lambda_{TV}^*)$.

Narratives whose coefficient paths and implied break dates remain stable across this range support a robust substantive interpretation; narratives whose paths or breakpoints move materially indicate sensitivity to smoothing strength within the statistically indistinguishable band. In fact, as Figure ?? shows, coefficient path shapes are highly robust to the wide window of λ under consideration.

Because the $\arg\max S$ criterion is computed on the full sample, its sampling properties are characterised via a circular block bootstrap ($B = 100$ draws, block length $\ell = 8$ trading days) across a log-spaced grid spanning λ^* to $10\lambda^*$. For each draw b I refit the fused Lasso at every grid point and record $S_b(\lambda)$. The bootstrap 1.5-SE window—the direct analogue of the (Friedman et al., 2010) 1-SE rule, adapted from prediction error to decomposition quality—is

$$\Lambda_{1.5SE} = \{\lambda : |\bar{S}(\lambda) - \bar{S}(\lambda^*)| \leq 1.5\widehat{SE}(S)\}.$$

The window is asymmetric around λ^* : $S(\lambda)$ drops steeply above λ^* (over-regularisation rapidly collapses genuine episodes) but gradually below it (re-emerging noise breaks degrade S only slowly). The operative bound for robustness is therefore the upper one.

I expand the 1-SE window (Hastie et al., 2009) by a conservative factor of 1.5 and refit the fused Lasso on an 81-point grid spanning the expanded window. I report the full path envelopes and the Jaccard similarity of the break set at each grid point relative to λ^* . A high Jaccard index across the window confirms that the identified regime-change dates are not an artefact of the precise penalty chosen.

Confidence intervals around λ^* : Residual wild block bootstrap. Because the contemporaneous design makes predictive cross-validation inapplicable, I assess sampling uncertainty in $\hat{\beta}_{k,t}$ and the break dates via a wild block bootstrap ($B = 500$, block length $\ell = 20$ trading days)¹⁸. Wild resampling—multiplying each drawn block by an independent Rademacher weight $w_j \in \{-1, +1\}$ —ensures genuine variance inflation even when fused Lasso residuals are small following the wild bootstrap logic used to restore

¹⁸With block length chosen to preserve overlap in dependence (Künsch, 1989; Politis and Romano, 1992). This follows the standard regression residual bootstrap idea for fixed regressors (Freedman, 1981), adapted to dependent data via blocking (Lahiri, 2003). Estimation is implemented in CVXPY (Diamond and Boyd, 2016) and solved with the Clarabel interior-point solver (Goulart and Chen, 2024)

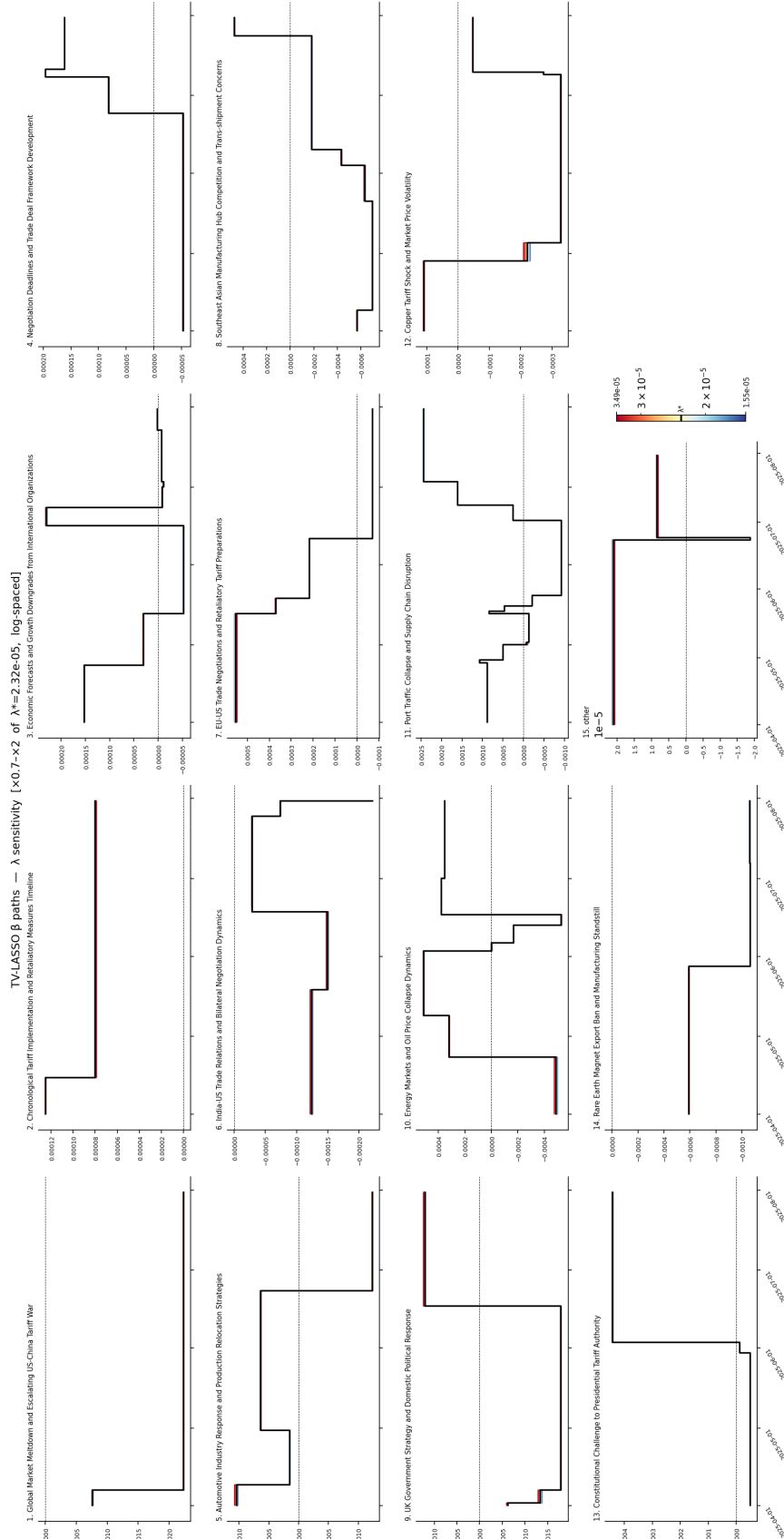


Figure D.4: λ_{TV} coefficient robustness

Step plots show β_t per article for each narrative (panels). In black is the coefficient path for λ_{TV}^* from the optimization programme; the coloured paths correspond to alternative λ_{TV} on a log grid within bootstrap-based bounds, with colour intensity denoting departure from λ_{TV}^* . Time ranges align with the trading-day estimation sample; the horizontal line marks zero. Narratives whose paths and implied breakpoints remain similar across λ_{TV} indicate robustness to the smoothness of the time-varying coefficients.

reasonable inference under conditional heteroskedasticity and related departures (Mammen, 1993; Davidson and Flachaire, 2008), here combined with blocking for dependence (see also Gonçalves and White, 2005). I report 95% confidence bands for each coefficient path in Figure D.5.

D.4 Estimated Narrative Signals F_{kt}

Figure D.6 presents the narrative signal loadings, $F_{kt} = \hat{\beta}_{kt} \times \text{number of articles}$, where β_{kt} is the narrative regime.

Bootstrap CI overview (95% band) | B=500, block=20, $\lambda_{TV}=2.32e-05$

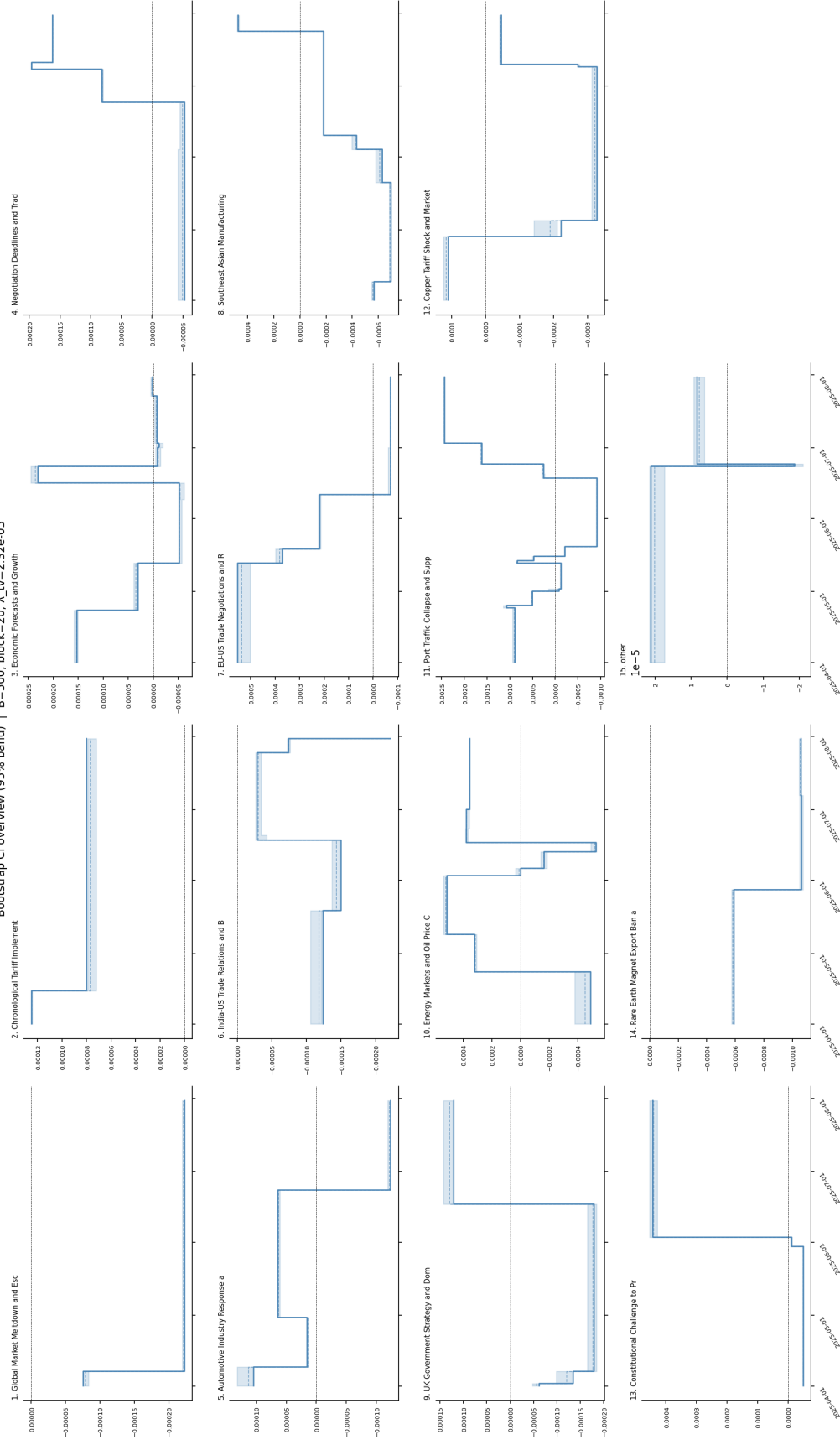


Figure D.5: λ_{TV} confidence bands

The panels display daily coefficients $\beta_{k,t}$ from the fused Lasso specification linking standardized narrative counts to the contemporaneous tariff price, one narrative per subplot (community labels in titles). The solid stepped line is the estimate on the original sample. The shaded band is the pointwise 95% confidence interval across bootstrap replications; the dashed stepped line is the bootstrap median path. Uncertainty is assessed by resampling residuals in contiguous blocks (with circular blocking to preserve serial dependence in shocks), reconstructing pseudo-outcomes holding regressors fixed, and re-estimating the model each replication; the regularization level is held fixed at the optimal λ_{TV}^* .

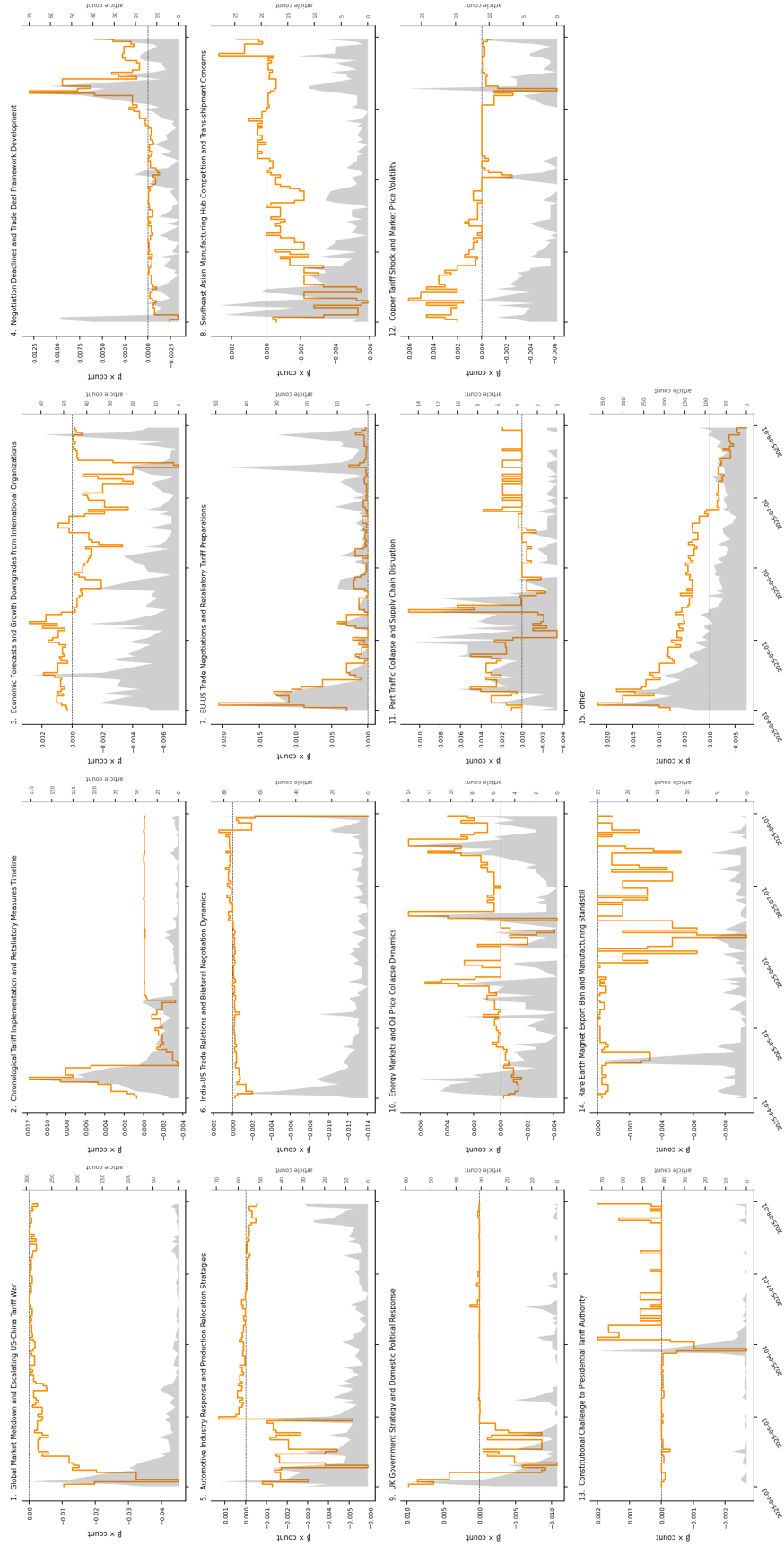


Figure D.6: Narrative Signals

Figure D.7: Narrative signals are given by the product of the per-article narrative regime $\hat{\beta}_{kt}$ and the number of articles in a narrative on a given day.

E Narrative Signals & Stocks' Exposure

E.1 Stocks' Exposure to Narrative Signals

NAICS	Industry	N	Narrative k															misc	max $ \Delta\gamma $
			0	1	2	3	4	5	6	7	8	9	10	11	12	13			
21	Mining & Oil/Gas	17	1.191	4.214	-0.944	0.103	-3.851	2.699	-1.562	3.364	1.783	-1.749	-0.633	-3.645	0.291	-0.364	11.906	3.20×10^{-14}	
22	Utilities	34	0.214	1.598	-0.102	-0.713	-3.311	0.660	-0.180	0.779	0.214	0.139	0.178	-2.020	-1.537	0.401	1.872	2.18×10^{-14}	
23	Construction	5	1.325	2.579	0.498	-0.172	-1.063	0.156	-2.856	0.571	-6.309	-3.534	-0.026	-5.965	-4.005	1.322	0.882	1.69×10^{-14}	
31	Food & Textile Mfg	25	0.647	1.646	-1.450	-0.150	-1.632	1.142	-0.542	0.929	0.048	-1.338	0.070	0.453	-2.558	0.176	3.602	4.53×10^{-14}	
32	Chemical & Plastics Mfg	45	0.697	2.350	-2.382	0.146	-2.628	2.164	-1.829	1.712	-1.053	-2.309	-0.150	-1.382	-2.408	0.085	7.756	1.41×10^{-13}	
33	Machinery & Electronics Mfg	110	-0.031	3.724	-1.638	-0.745	-3.034	2.229	-2.845	1.559	-2.747	-1.381	-0.071	-4.125	-0.737	0.689	5.073	1.76×10^{-13}	
42	Wholesale Trade	14	0.786	2.373	-1.297	-0.065	-2.281	1.676	-1.149	1.387	-1.137	-1.150	0.039	-1.224	-1.446	0.554	6.125	5.95×10^{-14}	
44	Retail – Vehicles/Building	7	0.618	1.882	-0.172	-0.502	-1.939	1.175	-0.895	0.786	-1.513	-1.111	0.412	-2.225	-1.021	1.254	1.697	9.77×10^{-15}	
45	Retail – General/Food	15	0.207	2.725	-0.798	-0.659	-1.829	0.342	-2.401	1.185	-3.321	-1.517	-0.337	-3.510	-1.787	0.542	3.347	2.49×10^{-14}	
48	Transportation	13	-0.075	4.393	-0.507	-0.561	-1.204	0.024	-4.223	0.836	-4.153	-1.983	-0.683	-4.989	-1.490	0.722	0.386	2.48×10^{-13}	
49	Warehousing & Couriers	4	1.003	3.644	-2.461	-0.487	-1.270	1.980	-2.684	1.123	-1.894	-2.377	-0.311	-1.454	-3.436	-0.285	5.429	6.31×10^{-14}	
51	Information	35	0.122	2.730	-1.465	-1.131	-3.059	1.454	-1.908	1.169	-1.650	-1.212	0.067	-2.649	-0.560	0.927	4.242	2.28×10^{-13}	
52	Finance & Insurance	66	0.214	2.957	-0.075	-0.765	-2.405	1.389	-1.891	0.914	-1.601	-0.823	-0.342	-2.146	-1.319	1.107	1.908	5.80×10^{-14}	
53	Real Estate	28	1.241	2.570	-0.774	-0.036	-1.060	1.575	-1.271	0.825	-0.523	-1.291	-0.092	-0.026	-2.192	0.249	4.158	5.60×10^{-14}	
54	Professional Services	26	0.620	3.148	-1.506	-0.775	-2.883	1.872	-2.114	1.560	-2.596	-1.240	-0.031	-2.443	-0.747	0.908	6.044	9.06×10^{-14}	
55	Management of Companies	4	0.670	3.415	-0.058	-0.476	-4.939	0.958	-2.475	1.230	-3.028	-1.920	-0.729	-4.390	-2.002	1.042	5.059	4.40×10^{-14}	
56	Admin & Support Services	20	0.103	2.999	-1.226	-1.237	-3.247	1.826	-2.001	1.435	-0.835	-1.855	0.053	-2.603	-0.776	0.744	4.558	2.31×10^{-14}	
62	Health Care	5	0.162	0.763	-1.853	-0.397	-1.792	1.323	-0.790	0.974	-1.038	-0.565	0.434	-0.776	-0.490	1.217	5.761	2.01×10^{-13}	
72	Accommodation & Food Svcs	10	0.630	3.148	-1.360	-0.232	-2.123	1.712	-2.796	1.067	-2.929	-2.377	-0.314	-2.808	-2.144	1.123	5.104	8.08×10^{-14}	
All 19 industries (285 loadings)			correlation = 1; entries agree at three decimals															2.48×10^{-13}	

Table E.1: Pooled OLS vs MixedLM Loading Estimation

Each entry is the industry loading γ_{gk} on narrative k . The mixed-model fixed effect and the slope from industry-pooled OLS of daily returns on the narrative signals and an intercept are the same number: they agree at the three decimals shown in every cell. $\max |\Delta\gamma|$ is the largest absolute difference across the 15 narratives in that industry, before rounding. The median absolute difference across all 285 loadings is 8.44×10^{-15} . N is the number of stocks. The gaps in the last column are numerical error. The correlation between the two vectors of 285 loadings is 1, and the largest absolute gap is 2.48×10^{-13} . Every stock is observed on all 84 trading days from 1 April to 31 July 2025, so pooled OLS is the regression of the equal-weighted industry return on the signals. Singleton industries NAICS 11 and 71 are omitted; those loadings are OLS in the main specification.

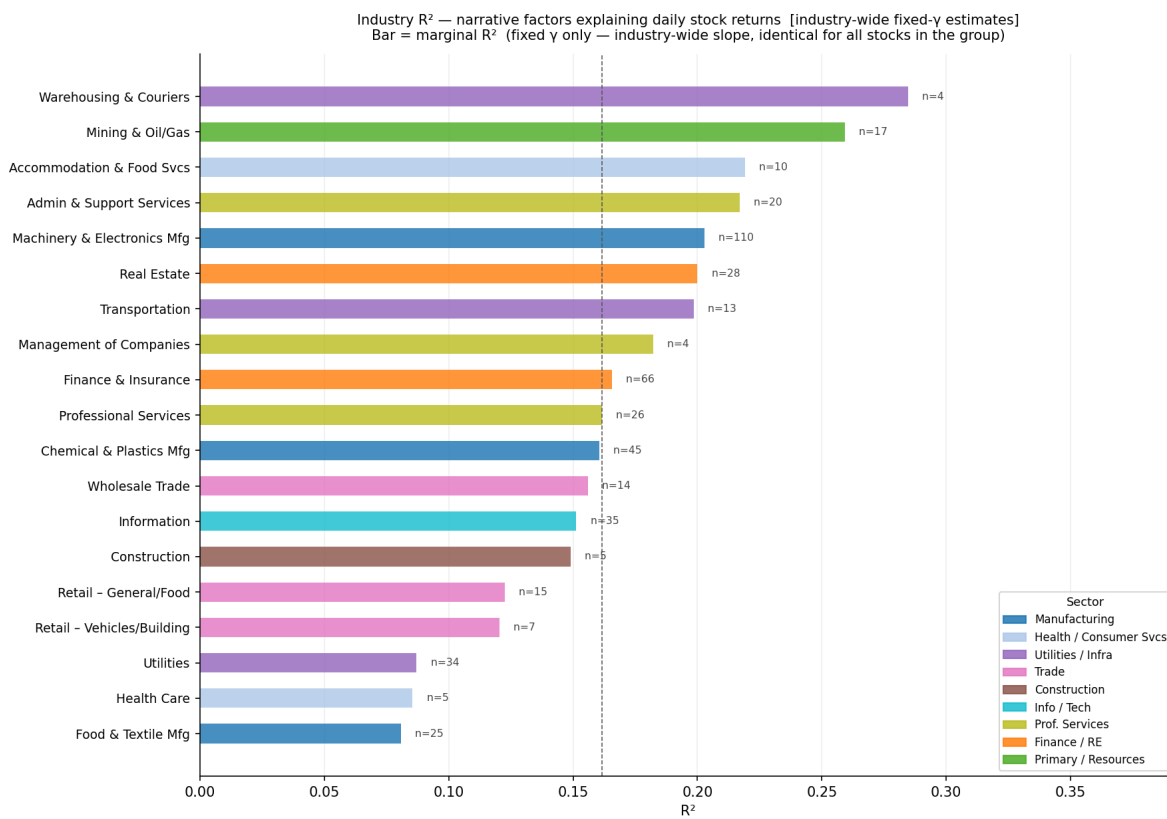


Figure E.1: Per-Industry R^2 of narrative signal pricing

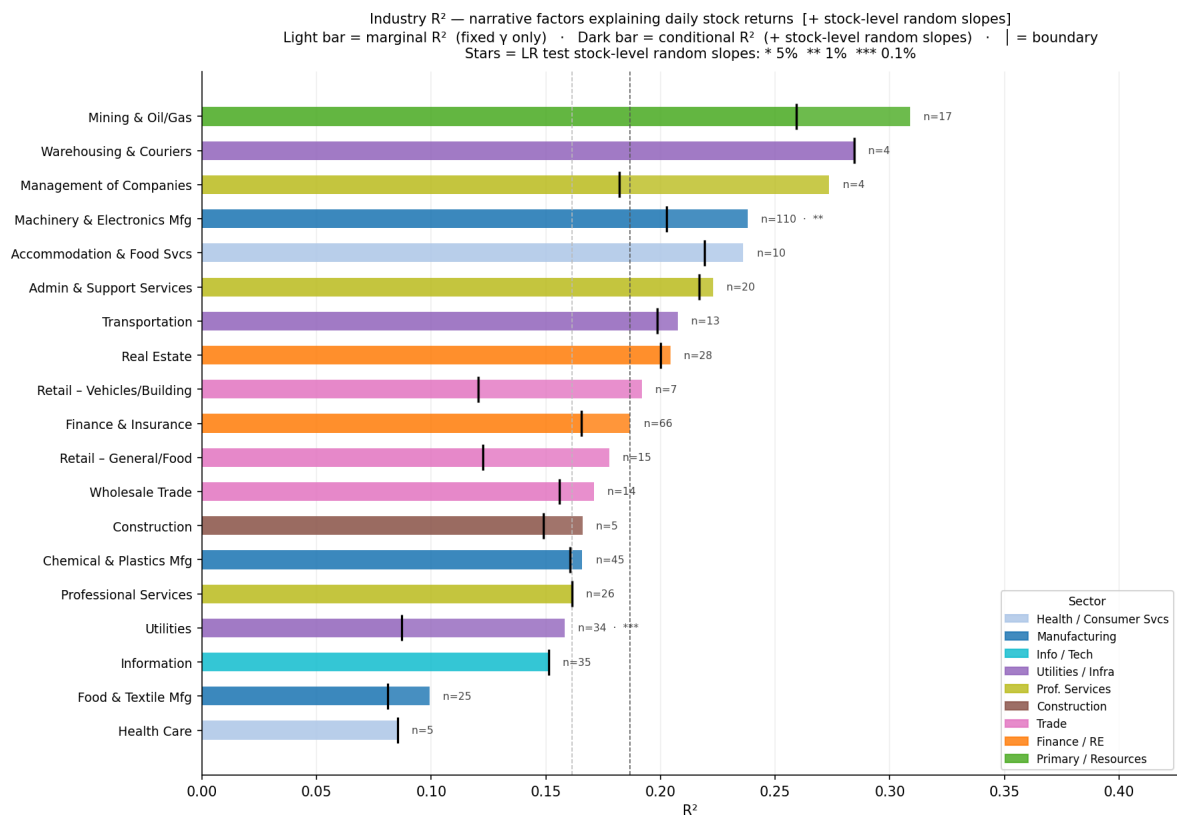


Figure E.2: Per-Industry R^2 of narrative signal pricing allowing for stock-specific loadings

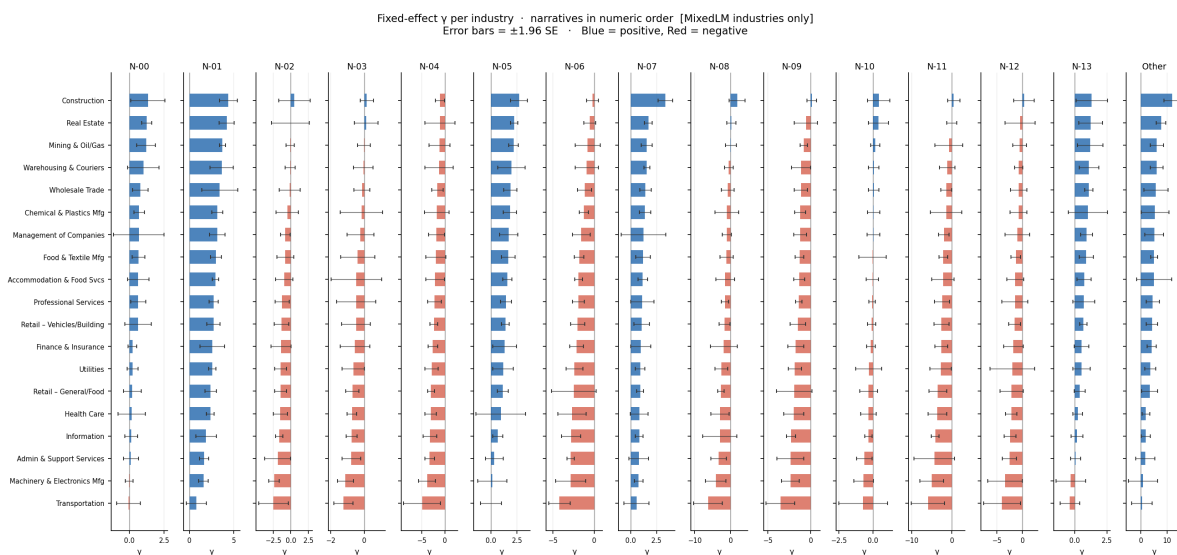


Figure E.3: Industry γ plots

Industries' exposures to each narrative.

	Narratives	Topic models				
Mean OOS R^2 (stock FE)	0.163	0.013	0.078	0.105	0.109	0.128
Mean OOS R^2 (no FE)	0.156	0.005	0.072	0.096	0.101	0.123
Text		Articles	Articles	Articles	Articles	Stories
Weight		Shares	Counts	Counts	Counts	Counts
K	15	5	5	15	15	15
Regimes	✓				✓	✓

Table E.2: Validation by cross-sectional held-out stocks

Each entry is the mean R^2 across 100 cross-sectional splits. Within each two-digit NAICS industry, half the stocks are held out. Industry loadings γ_g are estimated by pooled OLS on the training stocks only, then assigned to the held-out stocks in the same industry and on the same dates. The regressor is the predicted return $\sum_k \gamma_{k,g(i)} F_{k,t}$. The slope on that prediction is estimated on the held-out stock-days. The stock-FE row is the within R^2 after demeaning by stock. The no-FE row is the R^2 from the same regression with an intercept and no stock demeaning. Topic-model columns use the same splits and the same estimator, with LDA signals in place of the narrative signals (Appendix I). They start from the implementation closest to [Bybee et al. \(2024\)](#) (full article text; prominence captured by shares; 5 topics selected by a LASSO for their ability to explain stock returns; no regimes, so the topic weight is constant) and work up to a hybrid that stays closest to the narrative pipeline except that the signals are still topics (stories from step 1 as the text; article counts as weights; 15 topics selected by topic size; regimes). Text is the corpus, Weight is how prominence is measured, and K is the number of signals (where $K = 5$ are selected by a LASSO for their quality of fit, and $K = 15$ selected by pure prominence). A check under Regimes means the signal weights are piecewise constant. The narrative column uses fifteen piecewise-constant signals: fourteen tariff narratives and a residual category. The sample is 483 S&P 500 constituents and 84 trading days from 1 April to 31 July 2025. Returns are daily returns.

E.2 Narrative Disagreement & Narrative Cacophony

Figure E.4 presents the narrative disagreement measures, where:

Definition E.1. The *total realized narrative-implied tariff exposure* of narrative-driven price pressure (Figure E.4a) is given by:

$$\tau_{i,t} = \sum_{k=1}^K |c_{i,k,t}|, \quad (5)$$

Definition E.2. *Narrative dispersion* (Figure E.4b) is defined via the Shannon entropy of the normalized exposure shares. For $\rho_{i,k,t} = \frac{|c_{i,k,t}|}{\sum_{k'} |c_{i,k',t}|} \in [0, 1]$.¹⁹

$$H_{i,t} = - \sum_{k=1}^K \rho_{i,k,t} \log \rho_{i,k,t}, \quad (6)$$

which has codomain $[0, \log K]$. $H_{i,t} = 0$ if all of a stock's realized tariff exposure on day t are concentrated in a single narrative; as there are 15 narratives, $H_{i,t} = \log 15 \approx 2.71$ if narrative loadings are dispersed and all 15 narratives contribute equally. The median stock-day has $H_{i,t} = 1.98$, or about 73% of the maximal value. This corresponds to $e^{1.98} \approx 7.24$ effective equal narratives on the median stock.

Definition E.3. *Directional disagreement* (Figure E.4c) is a measure of sign conflict:

$$D_{i,t} = 1 - \frac{|\sum_k c_{i,k,t}|}{\sum_k |c_{i,k,t}|} \in [0, 1]. \quad (7)$$

That is, polarization captures the share of narratives which contradict each other (i.e., cancel out) irrespective of the level of pressure they exert or their number. $D_{i,t} = 0$ if all active narratives predict the same direction for stock i (full alignment); $D_{i,t} = 1$ if positive and negative narratives perfectly cancel. The median $D_{i,t}$ is 0.75, meaning that on a typical stock-day, 75% of the gross narrative exposure cancels between opposing-direction narratives – reflecting the genuine directional tension in the 2025 tariff narrative space.

Definition E.4. *Narrative cacophony* (Figure E.4d) is characterized by the presence of many narratives with contradictory pricing implications:

$$\text{narrative cacophony}_{i,t} = H_{i,t} \times D_{i,t}. \quad (8)$$

¹⁹This and the following definition are, of course, valid only if $\tau_{i,t} = \sum_k |c_{i,k,t}| \neq 0$. This is never a binding constraint in the data. If it were, it would be natural to “patch” undefined dispersion H and directional disagreement D by 0.

Conceptual differences are discussed in the main text of the paper.

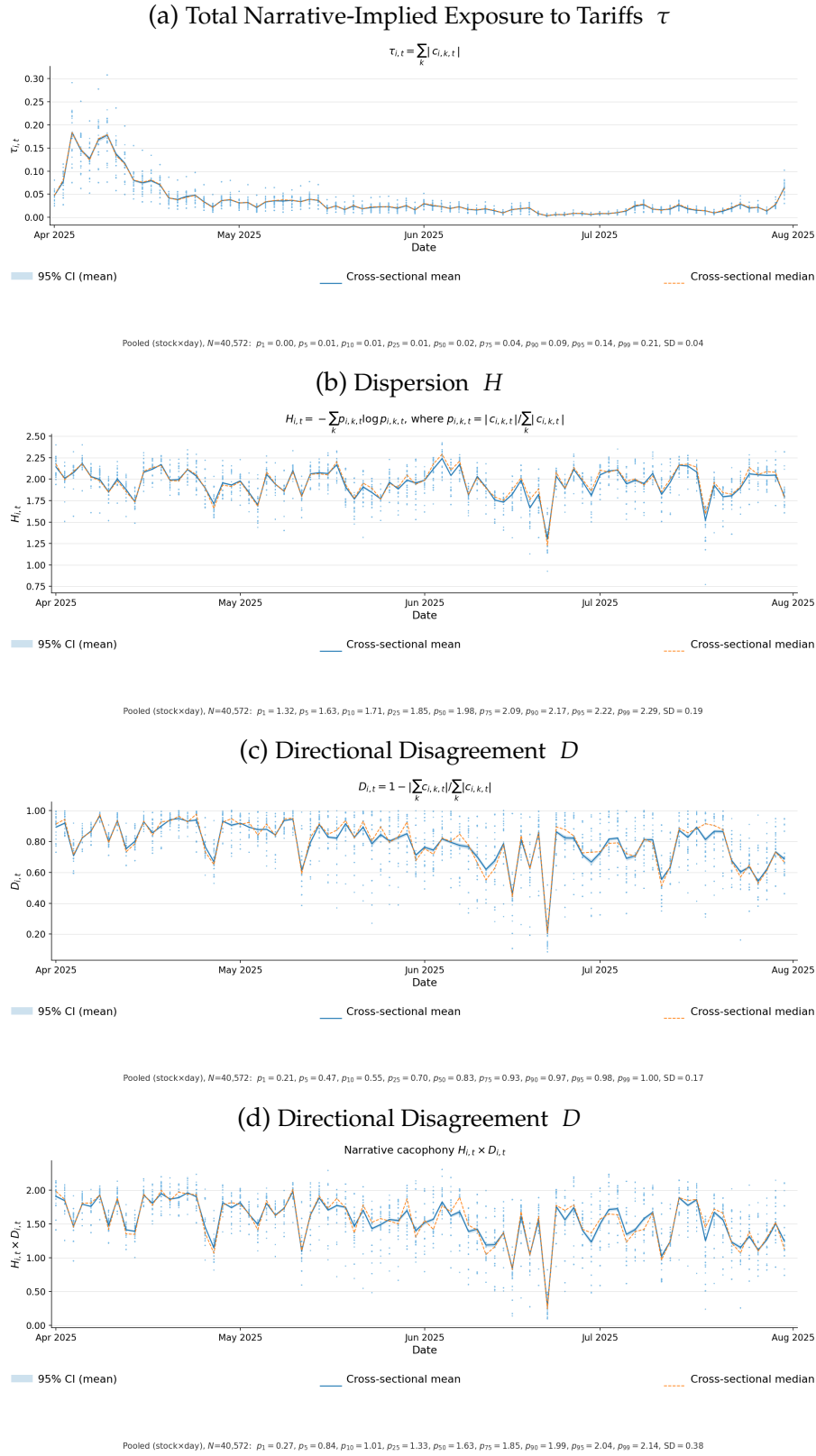


Figure E.4: Stock-level Measures of Narrative Disagreement & Cacophony

F Additional Tables, Figures, and Robustness Tests for Main Results

F.1 Hypothesis 1: Cacophony corresponds to lower volume

	(1)	(2)	(3)
Two-way cluster, industry and day	0.001***	0.005***	0.003***
Two-way cluster, industry and day, wild bootstrap	0.022**	0.025**	0.022**
One-way cluster, industry, wild bootstrap	0.001***	0.003***	0.002***
Two-way cluster, stock and day	<0.001***	0.003***	0.002***
One-way cluster, stock	<0.001***	<0.001***	<0.001***
Driscoll–Kraay, 3-day lag	0.001***	0.009***	0.004***
Driscoll–Kraay, 5-day lag	0.001***	0.010**	0.005***
Moving-block bootstrap, 5-day blocks	0.053*	0.019**	0.025**

Table F.1: Clustering robustness for the cacophony-volume effect

Each entry is the p -value on cacophony, $H_{i,t} \times D_{i,t}$. The dependent variable is log turnover. Every column also controls for dispersion $H_{i,t}$, directional disagreement $D_{i,t}$, narrative price pressure $\tau_{i,t}$, the absolute return $|r_{i,t}|$, and lagged log turnover $\ln \text{TO}_{i,t-1}$, and includes stock fixed effects. Column (2) adds $\ln(1+\text{no. articles}_i)$. Column (3) adds the commodity long-short return. Within a column, the rows change the covariance estimator. Two-way rows use Cameron–Gelbach–Miller clustering on the named dimensions. The industry wild bootstrap redraws Rademacher weights across the 19 two-digit NAICS industries ($B = 1,999$); the industry-and-day row applies that redraw to the two-way t -statistic, and the industry row applies it to the one-way industry t -statistic. Driscoll–Kraay standard errors use a Bartlett kernel. The moving-block bootstrap redraws circular five-day blocks of the cross-section and re-estimates the full specification. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion $H_{i,t}$	-0.082 (0.126)	0.835*** (0.202)	0.495*** (0.143)	0.456*** (0.119)	0.477*** (0.160)	0.456*** (0.149)
Directional Disagreement $D_{i,t}$	0.058 (0.375)	2.016*** (0.501)	1.221*** (0.390)	1.106*** (0.344)	1.137*** (0.410)	1.198*** (0.396)
Cacophony $H_{i,t} \times D_{i,t}$	-0.020 (0.207)	-1.116*** (0.260)	-0.675*** (0.203)	-0.656*** (0.178)	-0.673*** (0.209)	-0.695*** (0.201)
Narrative Price Pressure $\tau_{i,t}$				2.109*** (0.477)	2.330*** (0.842)	2.298*** (0.782)
$\ln(1+\text{no. articles}_t)$					-0.017 (0.071)	-0.018 (0.065)
Commodity long-short return						-11.351** (5.183)
$ r_{i,t-1} $		-1.336* (0.771)	1.120 (0.801)	-0.002 (0.629)	0.001 (0.630)	-0.109 (0.572)
$\ln \text{TO}_{i,t-1}$		0.840*** (0.020)	0.508*** (0.041)	0.469*** (0.034)	0.468*** (0.034)	0.473*** (0.037)
Stock FE			✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572
Within R^2	0.001	0.666	0.276	0.314	0.314	0.326
Overall R^2	0.001	0.666	0.717	0.732	0.732	0.736
$\partial \log \text{TO} / \partial H$ evaluated at:						
$D = 0.553$ (p10)	-0.093	0.218	0.122	0.093	0.105	0.072
$D = 0.698$ (p25)	-0.096	0.056	0.024	-0.003	0.008	-0.029
$D = 0.827$ (p50)	-0.098	-0.088	-0.063	-0.087	-0.079	-0.119
$D = 0.926$ (p75)	-0.100	-0.198	-0.130	-0.152	-0.146	-0.187
$D = 0.968$ (p90)	-0.101	-0.245	-0.158	-0.180	-0.174	-0.216
Sample share $\partial \log \text{TO} / \partial H > 0$	0.0%	33.2%	31.4%	24.8%	26.3%	21.0%
$\partial \log \text{TO} / \partial D$ evaluated at:						
$H = 1.71$ (p10)	0.025	0.108	0.066	-0.017	-0.014	0.011
$H = 1.846$ (p25)	0.022	-0.044	-0.026	-0.106	-0.105	-0.084
$H = 1.977$ (p50)	0.019	-0.190	-0.114	-0.192	-0.193	-0.175
$H = 2.092$ (p75)	0.017	-0.318	-0.192	-0.267	-0.271	-0.255
$H = 2.172$ (p90)	0.016	-0.407	-0.246	-0.320	-0.324	-0.310
Sample share $\partial \log \text{TO} / \partial D > 0$	100.0%	19.5%	19.6%	8.2%	8.2%	11.0%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.2: Narrative Cacophony and Volume, with lagged absolute returns

The dependent variable everywhere is log turnover. Dispersion $H_{i,t}$ is measured by the entropy of stock i 's distribution of narrative price shocks on day t ; directional disagreement $D_{i,t}$ measures the sign conflict of those narratives' price implications by the share of narrative price implications which survive a "netting out"; and cacophony is their product. Column (1) includes only these three terms. Column (2) adds the lagged return and lagged log turnover. Columns (3)–(6) add stock fixed effects and the rest of the controls: Column (4) adds narrative-implied tariff exposure $\tau_{i,t}$, column (5) the log number of articles, and column (6) the return on the commodity long-short tariff portfolio. The lower panels evaluate $\partial \log \mathcal{V} / \partial H$ at percentiles of D and $\partial \log \mathcal{V} / \partial D$ at percentiles of H , and report the share of stock-days on which each marginal effect is positive.

	High τ	High HTS		HTS available			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dispersion $H_{i,t}$	0.434** (0.213)	0.430** (0.199)	0.413** (0.184)	0.471** (0.190)	0.471** (0.190)	0.495** (0.207)	0.493** (0.208)
Directional Disagreement $D_{i,t}$	1.318** (0.519)	1.278*** (0.477)	1.319*** (0.449)	1.392*** (0.480)	1.390*** (0.473)	1.341*** (0.506)	1.362*** (0.509)
Cacophony $H_{i,t} \times D_{i,t}$	-0.720*** (0.270)	-0.707*** (0.250)	-0.717*** (0.234)	-0.766*** (0.246)	-0.765*** (0.243)	-0.753*** (0.263)	-0.762*** (0.264)
Narrative Price Pressure $\tau_{i,t}$	0.484 (0.974)	0.323 (0.884)	0.280 (0.800)	0.482 (0.833)	0.479 (0.825)	0.517 (0.919)	0.538 (0.914)
$\ln(1+\text{no. articles}_t)$	0.004 (0.091)	0.013 (0.083)	0.010 (0.078)	-0.008 (0.078)	-0.008 (0.078)	-0.007 (0.084)	-0.006 (0.084)
Commodity long-short return			-10.138** (4.986)	-10.530** (4.913)	-10.595** (5.111)		
$ r_{i,t} $	7.674*** (0.897)	7.893*** (0.749)	7.865*** (0.660)	7.810*** (0.786)	7.813*** (0.786)	7.865*** (0.881)	7.838*** (0.888)
$\ln \text{TO}_{i,t-1}$	0.413*** (0.028)	0.433*** (0.028)	0.433*** (0.029)	0.432*** (0.029)	0.432*** (0.029)	0.427*** (0.028)	0.431*** (0.028)
HTS $_{g,t}$	-0.238 (0.203)	-0.265* (0.160)	-0.050 (0.199)		0.028 (0.236)		-0.251 (0.189)
Stock FE	✓	✓	✓	✓	✓	✓	✓
N	11,986	6,972	6,972	13,918	13,918	13,918	13,918
Within R^2	0.430	0.449	0.458	0.442	0.442	0.432	0.432
Overall R^2	0.800	0.827	0.830	0.801	0.801	0.797	0.798
$\partial \log \text{TO} / \partial H$ evaluated at:							
$D = 0.553$ (p10)	0.036	0.039	0.017	0.048	0.048	0.078	0.072
$D = 0.698$ (p25)	-0.069	-0.064	-0.087	-0.063	-0.062	-0.031	-0.039
$D = 0.827$ (p50)	-0.162	-0.155	-0.180	-0.162	-0.161	-0.128	-0.137
$D = 0.926$ (p75)	-0.233	-0.225	-0.251	-0.238	-0.237	-0.203	-0.212
$D = 0.968$ (p90)	-0.263	-0.255	-0.281	-0.270	-0.269	-0.234	-0.244
Sample share $\partial \log \text{TO} / \partial H > 0$	15.8%	15.9%	11.2%	15.8%	15.8%	21.0%	19.1%
$\partial \log \text{TO} / \partial D$ evaluated at:							
$H = 1.71$ (p10)	0.086	0.069	0.093	0.083	0.083	0.053	0.059
$H = 1.846$ (p25)	-0.012	-0.027	-0.004	-0.021	-0.021	-0.049	-0.045
$H = 1.977$ (p50)	-0.107	-0.120	-0.098	-0.121	-0.121	-0.148	-0.144
$H = 2.092$ (p75)	-0.189	-0.201	-0.181	-0.209	-0.209	-0.235	-0.232
$H = 2.172$ (p90)	-0.247	-0.258	-0.238	-0.270	-0.270	-0.295	-0.293
Sample share $\partial \log \text{TO} / \partial D > 0$	23.6%	17.5%	22.9%	21.0%	21.0%	17.0%	18.0%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Standard errors, in parentheses, are two-way clustered by stock and by day.

Table F.3: Narrative Cacophony and Volume: Tariff-Exposure Subsamples

The dependent variable everywhere is log volume. Dispersion $H_{i,t}$, directional disagreement $D_{i,t}$, and cacophony $H_{i,t} \times D_{i,t}$. Every column includes stock fixed effects, narrative-implied tariff exposure $\tau_{i,t}$, absolute return, lagged log turnover, and the log number of articles, and is estimated on stock-days for which daily statutory tariff exposure is observed. Column (1) keeps stocks in the upper half of the distribution of narrative-implied tariff exposure τ_i and controls for daily statutory exposure HTS $_{g,t}$. Columns (2) and (3) keep stocks above the median of average statutory tariff exposure. Column (2) controls for HTS $_{g,t}$; column (3) also includes the return on the commodity long-short tariff portfolio. Columns (4)–(7) use the full set of stock-days on which daily statutory exposure is observed. Columns (4) and (5) include the commodity long-short return, columns (5) and (7) control for HTS $_{g,t}$, and column (6) uses only the common controls. The lower panels evaluate $\partial \log \mathcal{V} / \partial H$ at percentiles of D and $\partial \log \mathcal{V} / \partial D$ at percentiles of H , and report the share of stock-days in that column's sample on which each marginal effect is positive.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
H (own / alt. analogue)	0.418*** (0.028)	-0.481*** (0.104)	0.023 (0.016)	-2.233*** (0.112)	-0.552* (0.319)	0.089*** (0.013)	-0.889*** (0.147)	-1.737*** (0.170)	-4.133*** (0.105)	-3.264*** (0.747)
D (own / alt. analogue)	1.127*** (0.068)	-1.017*** (0.174)	0.259*** (0.031)	-3.682*** (0.186)	-1.992** (0.785)	0.361*** (0.038)	-1.702*** (0.369)	-3.324*** (0.281)	-6.869*** (0.174)	-8.755*** (1.777)
$H \times D$ (own / alt. analogue)	-0.647*** (0.036)	0.714*** (0.126)	-0.207*** (0.028)	2.613*** (0.134)	0.735** (0.339)	-0.291*** (0.030)	0.763*** (0.166)	2.372*** (0.206)	4.923*** (0.126)	3.625*** (0.782)
τ (own / alt. analogue)	-0.153 (0.108)	-0.400 (0.378)	-5.298*** (0.483)	-0.037 (0.123)	0.076* (0.041)	4.037*** (0.310)	0.004 (0.044)	0.764* (0.426)	0.827*** (0.175)	0.270*** (0.048)
$ r_{i,t} $	8.223*** (0.129)	8.243*** (0.126)	8.290*** (0.127)	8.226*** (0.131)	8.160*** (0.130)	8.070*** (0.126)	8.205*** (0.129)	8.212*** (0.126)	8.018*** (0.129)	8.036*** (0.128)
$\ln \text{TO}_{i,t-1}$	0.434*** (0.008)	0.426*** (0.008)	0.425*** (0.008)	0.425*** (0.008)	0.425*** (0.008)	0.424*** (0.008)	0.425*** (0.008)	0.426*** (0.008)	0.424*** (0.008)	0.424*** (0.008)
$\ln(1+\text{no. articles}_t)$	-0.044*** (0.006)	-0.045*** (0.004)	-0.058*** (0.004)	-0.024*** (0.006)	-0.054*** (0.007)	-0.081*** (0.005)	-0.055*** (0.006)	-0.047*** (0.004)	-0.038*** (0.007)	-0.073*** (0.008)
Tariff L-S Portfolio Return R_t^{LS}	-9.793*** (0.306)	-9.300*** (0.314)	-10.134*** (0.323)	-7.226*** (0.314)	-9.079*** (0.307)	-8.121*** (0.360)	-8.979*** (0.314)	-9.077*** (0.319)	-6.098*** (0.304)	-8.436*** (0.319)
VIX _{t}	0.000 (0.000)	-0.001*** (0.000)	-0.001* (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.000 (0.000)	-0.002*** (0.000)	-0.001** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)
Daily TPU _{t}	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
(ask – bid)/mid _{t}	-0.671 (7.021)	0.077 (7.076)	-1.481 (7.090)	-1.341 (7.141)	-0.028 (7.089)	0.357 (6.962)	0.380 (7.025)	1.458 (7.039)	-4.149 (7.007)	-0.138 (7.066)
Article unit		shares	shares	counts	counts	counts	counts	shares	counts	counts
Factor number		top 5	top 5	top 5	top15	top 5	top15	top 5	top 5	top15
Selection		lasso	lasso	lasso	prominence	lasso	prominence	lasso	lasso	prominence
Time-varying regimes			✓			✓		✓		
Industry-specific exposure		✓	✓	✓	✓	✓	✓		✓	✓
Stock FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572
Within R^2	0.460	0.454	0.455	0.463	0.455	0.458	0.456	0.455	0.471	0.456

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.4: Narrative Cacophony and Volume: Article-Topic Horse Race

The dependent variable everywhere is log volume. Every column includes absolute return, lagged log turnover, the log number of articles, the return on the commodity long-short tariff portfolio, the VIX, the daily trade-policy uncertainty index, the relative bid-ask spread, and stock fixed effects. Column (1) is the paper's narrative measures (dispersion H , directional disagreement D , cacophony $H \times D$ and narrative-implied tariff exposure τ). Columns (2)–(10) replace H , D , $H \times D$, and τ with the analogous quantities constructed from LDA topics estimated on articles. The rows beneath the estimates record how each alternative is built: article weights computed as shares (of total articles) or counts (number of articles), the five LASSO-selected topics (as being most relevant to returns) or the fifteen most prominent by size/count, the use of time-varying regimes or constant-imposed assumption, and industry-specific exposure or common-across-all-stocks loadings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dispersion $H_{i,t}$	0.418*** (0.028)	0.187*** (0.028)	0.427*** (0.028)	0.406*** (0.028)	0.426*** (0.029)	0.411*** (0.028)	0.422*** (0.029)	0.408*** (0.029)	0.434*** (0.029)	0.429*** (0.028)	0.419*** (0.028)
Directional Disagreement $D_{i,t}$	1.127*** (0.068)	0.572*** (0.067)	1.147*** (0.067)	1.116*** (0.068)	1.157*** (0.069)	1.080*** (0.068)	1.180*** (0.068)	1.147*** (0.068)	1.231*** (0.068)	1.118*** (0.067)	1.191*** (0.068)
Cacophony $H_{i,t} \times D_{i,t}$	-0.647*** (0.036)	-0.353*** (0.036)	-0.652*** (0.036)	-0.639*** (0.036)	-0.663*** (0.037)	-0.628*** (0.036)	-0.666*** (0.037)	-0.642*** (0.036)	-0.685*** (0.036)	-0.648*** (0.036)	-0.661*** (0.036)
Narrative Price Pressure $\tau_{i,t}$	-0.153 (0.108)	0.059 (0.108)	-0.715*** (0.144)	-0.225** (0.113)	-0.225* (0.116)	-0.170 (0.124)	-1.359*** (0.193)	-0.706*** (0.120)	-0.853*** (0.159)	-0.367*** (0.125)	-1.122*** (0.162)
$ r_{i,t} $	8.223*** (0.129)	7.967*** (0.129)	8.046*** (0.129)	8.231*** (0.130)	8.249*** (0.129)	8.196*** (0.131)	8.115*** (0.130)	8.129*** (0.128)	8.189*** (0.129)	8.123*** (0.130)	8.046*** (0.128)
$\ln \text{TO}_{i,t-1}$	0.434*** (0.008)	0.444*** (0.008)	0.437*** (0.008)	0.435*** (0.008)	0.433*** (0.008)	0.433*** (0.008)	0.438*** (0.008)	0.433*** (0.008)	0.436*** (0.008)	0.433*** (0.008)	0.437*** (0.008)
$\ln(1+\text{no. articles}_i)$	-0.044*** (0.006)	-0.021*** (0.006)	-0.086*** (0.007)	-0.042*** (0.006)	-0.055*** (0.006)	-0.040*** (0.006)	-0.077*** (0.007)	-0.071*** (0.006)	-0.055*** (0.006)	-0.065*** (0.007)	-0.104*** (0.008)
Tariff L-S Portfolio Return R_i^{LS}	-9.793*** (0.306)	-8.766*** (0.301)	-9.709*** (0.331)	-9.814*** (0.320)	-10.655*** (0.331)	-8.837*** (0.309)	-8.994*** (0.320)	-7.540*** (0.364)	-8.942*** (0.331)	-8.876*** (0.306)	-8.770*** (0.322)
VIX _t	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.001* (0.000)	-0.000 (0.000)	0.001* (0.000)	0.002*** (0.000)	0.000 (0.000)	-0.001* (0.000)	0.000 (0.000)
Daily TPU _t	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
(ask – bid)/mid _{i,t}	-0.671 (7.021)	1.688 (7.019)	0.627 (7.036)	-0.772 (7.029)	-1.773 (7.031)	1.299 (7.059)	-0.213 (7.078)	0.122 (6.974)	-0.035 (7.007)	1.241 (7.078)	-0.045 (7.051)
Article unit		shares	counts	shares	shares	counts	counts	counts	counts	counts	counts
Factor number		top 5	top 5	top 5	top 5	top 5	top15	top 5	top15	top 5	top15
Selection		lasso	lasso	lasso	lasso	lasso	prominence	lasso	prominence	lasso	prominence
Time-varying regimes					✓			✓	✓		
Industry-specific exposure				✓	✓	✓	✓	✓	✓		
Stock FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572
Within R ²	0.460	0.471	0.462	0.460	0.461	0.462	0.461	0.463	0.462	0.463	0.463

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.5: Narrative Cacophony and Volume: Article Topics as Controls

The dependent variable everywhere is log volume. Every column includes Dispersion $H_{i,t}$, directional disagreement $D_{i,t}$, and cacophony $H_{i,t} \times D_{i,t}$, narrative-implied tariff exposure $\tau_{i,t}$, absolute return, lagged log turnover, the log number of articles, the return on the commodity long-short tariff portfolio, the VIX, the daily trade-policy uncertainty index, the relative bid-ask spread, and stock fixed effects. Columns (2)–(11) add, as further controls: dispersion, directional disagreement, cacophony, and the exposure measure constructed from LDA topics estimated on articles. The rows beneath the estimates record how each alternative is built: article weights computed as shares (of total articles) or counts (number of articles), the five LASSO-selected topics (as being most relevant to returns) or the fifteen most prominent by size/count, the use of time-varying regimes or constant-imposed assumption, and industry-specific exposure or common-across-all-stocks loadings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
H (own / alt. analogue)	0.418*** (0.028)	-0.811*** (0.122)	0.013 (0.014)	-2.823*** (0.339)	0.538*** (0.074)	0.360*** (0.038)	0.042** (0.018)	-0.219*** (0.082)	-1.669*** (0.137)	-10.175*** (0.762)
D (own / alt. analogue)	1.127*** (0.068)	-1.916*** (0.198)	-0.185*** (0.039)	-8.153*** (0.848)	0.788*** (0.183)	-0.371 (0.574)	0.035 (0.026)	-15.520*** (1.830)	-3.389*** (0.223)	-27.181*** (1.918)
$H \times D$ (own / alt. analogue)	-0.647*** (0.036)	1.330*** (0.147)	0.140*** (0.032)	3.523*** (0.360)	-0.364*** (0.089)	0.193 (0.400)	-0.088*** (0.025)	11.244*** (1.348)	2.402*** (0.165)	11.508*** (0.805)
τ (own / alt. analogue)	-0.153 (0.108)	-0.518*** (0.119)	3.078*** (0.259)	0.078 (0.058)	0.412*** (0.125)	1.697*** (0.313)	-1.582*** (0.562)	1.095*** (0.320)	-0.753*** (0.130)	0.236*** (0.074)
$ r_{i,t} $	8.223*** (0.129)	8.249*** (0.129)	8.205*** (0.126)	8.216*** (0.130)	8.099*** (0.128)	8.282*** (0.127)	8.296*** (0.127)	8.210*** (0.126)	8.194*** (0.126)	8.067*** (0.127)
$\ln \text{TO}_{i,t-1}$	0.434*** (0.008)	0.424*** (0.008)	0.427*** (0.008)	0.425*** (0.008)	0.423*** (0.008)	0.426*** (0.008)	0.423*** (0.008)	0.424*** (0.008)	0.422*** (0.008)	0.424*** (0.008)
$\ln(1+\text{no. articles}_t)$	-0.044*** (0.006)	-0.005 (0.007)	-0.066*** (0.005)	-0.054*** (0.007)	-0.052*** (0.007)	-0.034*** (0.004)	-0.048*** (0.004)	-0.040*** (0.004)	0.008 (0.008)	-0.070*** (0.008)
Tariff L-S Portfolio Return R_t^{LS}	-9.793*** (0.306)	-9.237*** (0.302)	-7.905*** (0.399)	-9.315*** (0.311)	-9.303*** (0.320)	-9.179*** (0.301)	-9.655*** (0.300)	-9.362*** (0.307)	-9.341*** (0.306)	-8.566*** (0.324)
VIX_t	0.000 (0.000)	0.002*** (0.000)	-0.003*** (0.000)	0.001 (0.000)	-0.001*** (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)	0.003*** (0.000)	0.002*** (0.000)
Daily TPU _{t}	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
(ask – bid)/mid _{i,t}	-0.671 (7.021)	1.847 (7.016)	0.998 (7.080)	0.938 (6.983)	1.155 (7.108)	1.244 (7.071)	-0.173 (7.082)	1.787 (7.123)	2.387 (7.004)	1.336 (7.028)
Article unit		counts	counts	counts	counts	shares	shares	shares	counts	counts
Factor number		top 5	top 5	top15	top15	top 5	top 5	top 5	top 5	top15
Selection		lasso	lasso	prominence	prominence	lasso	lasso	lasso	lasso	prominence
Time-varying regimes			✓		✓		✓			
Industry-specific exposure		✓	✓	✓	✓	✓	✓		✓	
Stock FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572
Within R^2	0.460	0.457	0.455	0.458	0.458	0.456	0.456	0.458	0.459	0.461

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.6: Narrative Cacophony and Volume: Story-Topic Horse Race

The dependent variable everywhere is log volume. Every column includes absolute return, lagged log turnover, the log number of articles, the return on the commodity long-short tariff portfolio, the VIX, the daily trade-policy uncertainty index, the relative bid-ask spread, and stock fixed effects. Column (1) is the paper’s narrative measures (dispersion H , directional disagreement D , cacophony $H \times D$ and narrative-implied tariff exposure τ). Columns (2)–(10) replace H , D , $H \times D$, and τ with the analogous quantities constructed from LDA topics estimated on articles. The rows beneath the estimates record how each alternative is built: article weights computed as shares (of total articles) or counts (number of articles), the five LASSO-selected topics (as being most relevant to returns) or the fifteen most prominent by size/count, the use of time-varying regimes or constant-imposed assumption, and industry-specific exposure or common-across-all-stocks loadings. In this specification, all topic models take as input not the raw article texts, but the summarized “stories” so that the text input is identical to that of the narrative pipeline.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dispersion $H_{i,t}$	0.418*** (0.028)	0.422*** (0.028)	0.452*** (0.030)	0.423*** (0.029)	0.434*** (0.029)	0.455*** (0.029)	0.379*** (0.029)	0.474*** (0.029)	0.426*** (0.028)	0.444*** (0.029)	0.381*** (0.028)	0.449*** (0.028)
Directional Disagreement $D_{i,t}$	1.127*** (0.068)	1.178*** (0.068)	1.231*** (0.071)	1.251*** (0.071)	1.163*** (0.069)	1.229*** (0.071)	1.055*** (0.069)	1.286*** (0.070)	1.198*** (0.067)	1.379*** (0.071)	1.145*** (0.067)	1.220*** (0.068)
Cacophony $H_{i,t} \times D_{i,t}$	-0.647*** (0.036)	-0.668*** (0.036)	-0.702*** (0.038)	-0.693*** (0.038)	-0.655*** (0.037)	-0.706*** (0.038)	-0.606*** (0.037)	-0.736*** (0.037)	-0.677*** (0.036)	-0.739*** (0.038)	-0.623*** (0.036)	-0.693*** (0.036)
Narrative Price Pressure $\tau_{i,t}$	-0.153 (0.108)	-0.312** (0.139)	-0.374*** (0.114)	-1.304*** (0.176)	-1.296*** (0.168)	-0.298*** (0.112)	-0.171 (0.110)	-0.332*** (0.111)	-0.488*** (0.141)	-1.359*** (0.167)	-0.342*** (0.112)	-0.151 (0.138)
$ r_{i,t} $	8.223*** (0.129)	8.209*** (0.129)	8.192*** (0.128)	8.212*** (0.130)	8.113*** (0.130)	8.283*** (0.129)	8.255*** (0.130)	8.278*** (0.129)	8.192*** (0.128)	8.130*** (0.128)	8.315*** (0.128)	8.372*** (0.129)
$\ln \text{TO}_{i,t-1}$	0.434*** (0.008)	0.432*** (0.008)	0.437*** (0.008)	0.438*** (0.008)	0.434*** (0.008)	0.435*** (0.008)	0.431*** (0.008)	0.434*** (0.008)	0.432*** (0.008)	0.437*** (0.008)	0.432*** (0.008)	0.437*** (0.008)
$\ln(1 + \text{no. articles}_i)$	-0.044*** (0.006)	-0.010 (0.008)	-0.063*** (0.006)	-0.071*** (0.007)	-0.075*** (0.007)	-0.033*** (0.006)	-0.047*** (0.006)	-0.036*** (0.006)	-0.007 (0.008)	-0.122*** (0.008)	-0.045*** (0.006)	-0.064*** (0.007)
Tariff L-S Portfolio Return R_t^{LS}	-9.793*** (0.306)	-9.520*** (0.307)	-8.061*** (0.407)	-9.410*** (0.322)	-8.732*** (0.328)	-9.476*** (0.305)	-10.067*** (0.306)	-9.252*** (0.308)	-9.355*** (0.310)	-9.564*** (0.325)	-8.847*** (0.308)	-7.518*** (0.344)
VIX _t	0.000 (0.000)	0.002*** (0.000)	-0.001** (0.000)	0.002*** (0.000)	0.001* (0.000)	0.002*** (0.000)	0.000 (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.004*** (0.000)	0.004*** (0.001)
Daily TPU _t	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
(ask – bid)/mid _{i,t}	-0.671 (7.021)	0.458 (6.982)	0.802 (7.042)	-0.052 (6.972)	0.296 (7.166)	1.091 (6.989)	-0.705 (7.041)	1.196 (7.123)	0.428 (6.980)	0.939 (7.053)	2.024 (6.996)	3.727 (7.000)
Article unit		counts	counts	counts	counts	shares	shares	shares	counts	counts	shares	counts
Factor number		top 5	top 5	top15	top15	top 5	top 5	top 5	top 5	top15	top 5	top 5
Selection		lasso	lasso	prominence	prominence	lasso	lasso	lasso	lasso	prominence	lasso	lasso
Time-varying regimes			✓		✓		✓					
Industry-specific exposure		✓		✓	✓	✓	✓					
Stock FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572	40,572
Within R ²	0.460	0.463	0.462	0.464	0.465	0.463	0.461	0.465	0.464	0.468	0.473	0.464

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.7: Narrative Cacophony and Volume: Story Topics as Controls

The dependent variable everywhere is log volume. Every column includes Dispersion $H_{i,t}$, directional disagreement $D_{i,t}$, and cacophony $H_{i,t} \times D_{i,t}$, narrative-implied tariff exposure $\tau_{i,t}$, absolute return, lagged log turnover, the log number of articles, the return on the commodity long-short tariff portfolio, the VIX, the daily trade-policy uncertainty index, the relative bid-ask spread, and stock fixed effects. Columns (2)–(11) add, as further controls: dispersion, directional disagreement, cacophony, and the exposure measure constructed from LDA topics estimated on articles. The rows beneath the estimates record how each alternative is built: story weights computed as shares (of total articles) or counts (number of articles), the five LASSO-selected topics (as being most relevant to returns) or the fifteen most prominent by size/count, the use of time-varying regimes or constant-imposed assumption, and industry-specific exposure or common-across-all-stocks loadings. In this specification, all topic models take as input not the raw article texts, but the summarized “stories” so that the text input is identical to that of the narrative pipeline.

	(1)	(2)	(3)	(4)	(5)	(6)
$1 - \text{HHI}_{i,t}$	-0.244 (0.346)	2.095*** (0.490)	1.175*** (0.338)	1.143*** (0.331)	1.107** (0.439)	1.060*** (0.399)
Directional Disagreement $D_{i,t}$	0.359 (0.583)	2.506*** (0.603)	1.543*** (0.486)	1.495*** (0.492)	1.471** (0.580)	1.584*** (0.563)
$(1 - \text{HHI}_{i,t}) \times D_{i,t}$	-0.394 (0.739)	-3.253*** (0.729)	-1.979*** (0.581)	-1.943*** (0.583)	-1.912*** (0.688)	-2.030*** (0.665)
Narrative Price Pressure $\tau_{i,t}$				0.461 (0.397)	0.326 (0.806)	0.320 (0.738)
$\ln(1 + \text{no. articles}_t)$					0.010 (0.069)	0.008 (0.064)
Commodity long-short return						-10.264** (4.935)
$ r_{i,t} $		7.737*** (0.967)	8.312*** (0.754)	7.919*** (0.812)	7.931*** (0.809)	7.846*** (0.729)
$\ln \text{TO}_{i,t-1}$		0.760*** (0.017)	0.455*** (0.031)	0.445*** (0.028)	0.445*** (0.027)	0.448*** (0.028)
Stock FE			✓	✓	✓	✓
N	40,572	40,572	40,572	40,572	40,572	40,572
Within R^2	0.002	0.718	0.425	0.427	0.427	0.437
Overall R^2	0.002	0.718	0.775	0.776	0.776	0.780
$\partial \log \text{TO} / \partial (1 - \text{HHI})$ evaluated at:						
$D = 0.553$ (p10)	-0.462	0.296	0.081	0.069	0.049	-0.062
$D = 0.698$ (p25)	-0.519	-0.176	-0.206	-0.213	-0.228	-0.357
$D = 0.827$ (p50)	-0.570	-0.595	-0.462	-0.464	-0.474	-0.618
$D = 0.926$ (p75)	-0.609	-0.917	-0.658	-0.656	-0.664	-0.819
$D = 0.968$ (p90)	-0.625	-1.054	-0.741	-0.738	-0.744	-0.905
Sample share $\partial \log \text{TO} / \partial (1 - \text{HHI}) > 0$	0.0%	18.6%	13.4%	12.1%	11.6%	7.6%
$\partial \log \text{TO} / \partial D$ evaluated at:						
$(1 - \text{HHI}) = 0.742$ (p10)	0.067	0.093	0.075	0.053	0.052	0.078
$(1 - \text{HHI}) = 0.782$ (p25)	0.051	-0.037	-0.004	-0.024	-0.025	-0.003
$(1 - \text{HHI}) = 0.817$ (p50)	0.037	-0.151	-0.074	-0.092	-0.092	-0.074
$(1 - \text{HHI}) = 0.845$ (p75)	0.026	-0.242	-0.129	-0.147	-0.145	-0.131
$(1 - \text{HHI}) = 0.861$ (p90)	0.020	-0.294	-0.161	-0.178	-0.176	-0.163
Sample share $\partial \log \text{TO} / \partial D > 0$	100.0%	18.3%	24.0%	18.2%	18.1%	24.5%

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Standard errors, in parentheses, are two-way clustered by stock and by day.

Table F.8: Narrative Cacophony and Volume, with HHI diversity

The dependent variable everywhere is log volume. Dispersion is given, instead of the usual Shannon-entropy-derived construction, by the HHI diversity index, specifically: $1 - \text{HHI}_{i,t} = 1 - \sum_k p_{ikt}^2$, where p_{ikt} is stock i 's share of narrative price-shock mass on narrative k on day t . Directional disagreement $D_{i,t}$ is the share of narrative price implications that survive netting out, and the cacophony term is their product – as per the standard specifications. Column (1) includes only these three terms. Column (2) adds the absolute return and lagged log turnover. Columns (3)–(6) add stock fixed effects and the remaining controls: column (4) adds narrative-implied tariff exposure $\tau_{i,t}$, column (5) the log number of articles, and column (6) the return on the commodity long-short tariff portfolio. The lower panels evaluate $\partial \log \mathcal{V} / \partial (1 - \text{HHI})$ at percentiles of D and $\partial \log \mathcal{V} / \partial D$ at percentiles of $1 - \text{HHI}$, and report the share of stock-days on which each marginal effect is positive.

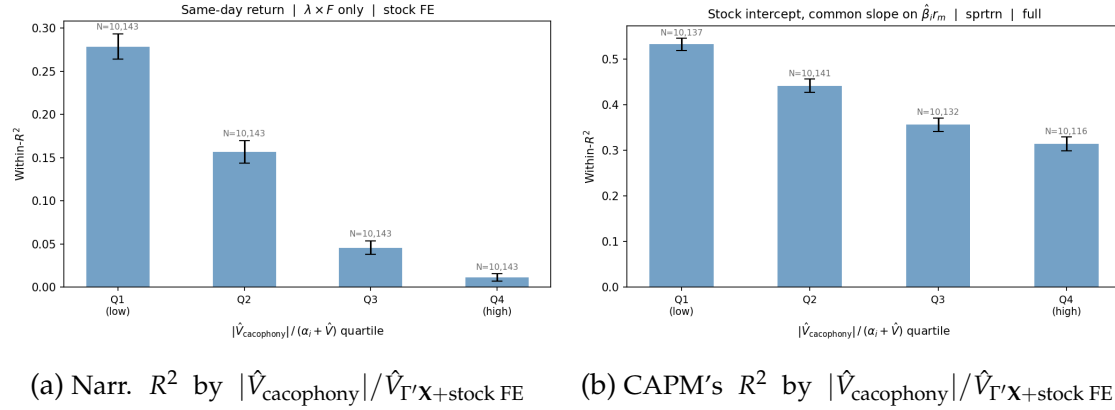


Figure F.1: S&P 500 Stocks Return R^2 by Quartile of Cacophony-Stified Volume Share

Stock-day observations are sorted by $|\hat{V}_{\text{cacophony}}| / \hat{V}$, where $\hat{V}_{\text{cacophony}} = \hat{\gamma}_{H \times D}(H \times D)$ is the contribution of the entropy $\times$ sign-conflict term to fitted log turnover. The denominator is the fitted volume with the stock FE, $\hat{V}_{\Gamma'X + \text{stock FE}}$. The left panel reports the within- R^2 from a regression of the same-day return on the narrative-signal prediction $\lambda_i' F_t$, with stock fixed effects and stock-by-stock slope. The right panel reports the adjusted R^2 from a CAPM estimation (with stock FEs). Error bars indicate 95% intervals, and N is the number of stock-days in the quartile.

F.2 Hypothesis 2: Cacophony and explanatory power of narratives

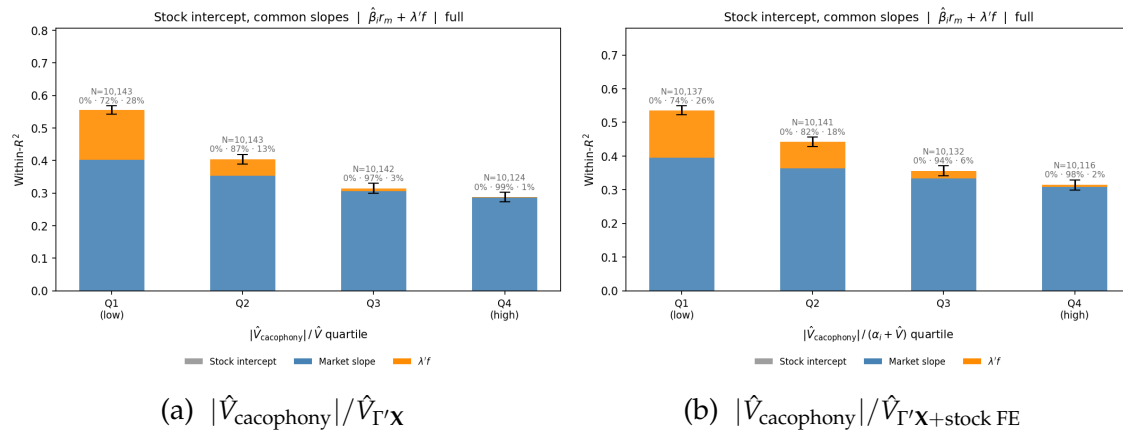


Figure F.2: CAPM and narrative signals, Shapley shares of the within- R^2

Each bar is the within- R^2 of $r_{it} = a_i + b, (\hat{\beta}_i r_{m,t}) + c, (\Lambda' \mathbf{F})_{it} + \varepsilon_{it}$, estimated inside the quartile. $\hat{\beta}_i$ and the loadings in Λ are full-sample estimates; the stock intercept a_i and the two common slopes are re-estimated in the quartile. The within- R^2 is computed after removing stock means, so the stock-intercept contribution is zero and the bar is the Shapley split between $\hat{\beta}_i r_{m,t}$ (blue) and $\Lambda' \mathbf{F}$ (orange). The annotation is the number of stock-days and those two shares, with the intercept share, of the within- R^2 . Whiskers are 95% intervals around the within- R^2 . Panel (a) sorts on $|\hat{V}_{\text{cac}}|/\hat{V}$ (slopes only), with the stock effect left out of fitted volume. Panel (b) sorts on $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$, with the stock effect included. Q1 is the lowest share and Q4 the highest. In both panels the within- R^2 falls across quartiles, and the narrative share of it falls from 28% to 1% in panel (a) and from 26% to 2% in panel (b).

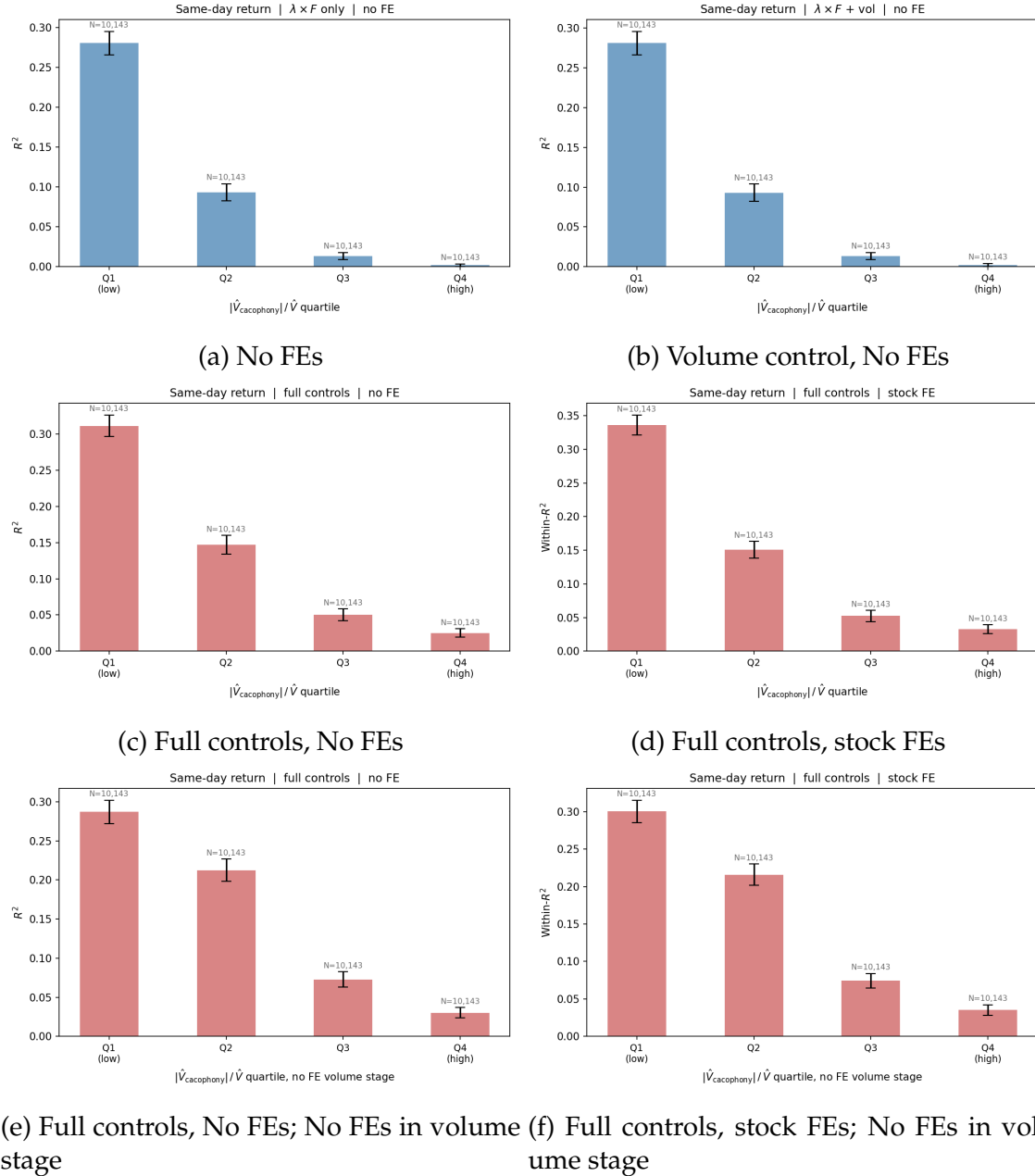


Figure F.3: R^2 by quartile of cacophony-suppressed volume

Each bar is the R^2 from a separate regression of the same-day return inside the corresponding quartile of $|\hat{V}_{\text{cacophony}}|/\hat{V}$. The numerator is the cacophony piece of fitted log volume, $|\hat{V}_{\text{cacophony}}| = |\hat{\gamma}_{H \times D}(H_{it} \times D_{it})|$, and $\hat{V}$ is the slope component of that fit. Q1 is the lowest cacophony-suppressed volume ratio and Q4 the highest. Each quartile has 10,143 stock-days. 95% confidence intervals for the R^2 are shown ($\hat{R}^2 \pm 1.95 \times 2\sqrt{\hat{R}^2(1 - \hat{R}^2)^2/N}$). Panel (a) uses only the narrative prediction $\lambda_t^i F_t$, no fixed effects. Panel (b) adds contemporaneous log turnover, $\ln(\text{volume}_{it}/\text{shares}_{it})$. Panels (c) and (d) include controls for H , D , $H \times D$, τ , the absolute return, lagged log turnover, the log number of articles, and the commodity long-short return. Panel (c) has no fixed effects, so the bar is the OLS R^2 . Panel (d) has stock fixed effects, so the bar is the within- R^2 . Panels (e) and (f) repeat (c) and (d), respectively, but excluding stock FEs from the first-stage volume analysis altogether.

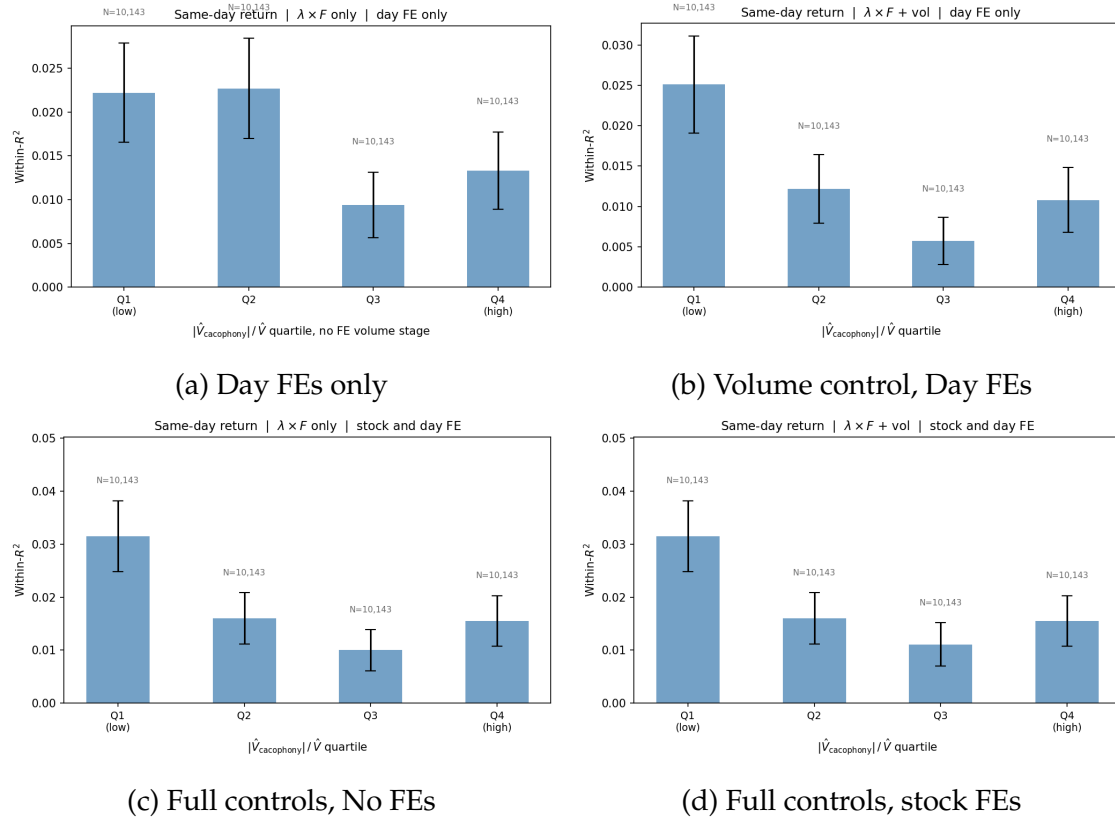


Figure F.4: R^2 by quartile of cacophony-suppressed volume: day FEs

Each bar is the R^2 from a separate regression of the same-day return inside the corresponding quartile of $|\hat{V}_{\text{cacophony}}|/\hat{V}$. The numerator is the cacophony piece of fitted log volume, $|\hat{V}_{\text{cacophony}}| = |\hat{\gamma}_{H \times D}(H_{it} \times D_{it})|$, and $\hat{V}$ is the slope component of that fit. Q1 is the lowest cacophony-suppressed volume ratio and Q4 the highest. Each quartile has 10,143 stock-days. 95% confidence intervals for the R^2 are shown ($\hat{R}^2 \pm 1.95 \times 2\sqrt{\hat{R}^2(1 - \hat{R}^2)^2/N}$). Panel (a) uses only the narrative prediction $\lambda_i^t F_t$, with day fixed effects. Panel (b) adds contemporaneous log turnover, $\ln(\text{volume}_{it}/\text{shares}_{it})$. Panel (c) and (d) repeat (a) and (b), respectively, but with two-way (stock, day) fixed effects.

F.3 Hypothesis 3: Cacophony and informational efficiency

	Q1	Q2	Q3	Q4	Q4–Q1 <i>p</i> -value
<i>No fixed effects</i>					
Same day, r_{it}	1.29***	0.78***	0.43**	0.27**	0.0002***
Same day, r_{it} (controls)	1.31***	0.78***	0.45**	0.30**	0.0002***
Next day, $r_{i,t+1}$	0.14	0.41	0.48*	0.50*	0.148
Next day, $r_{i,t+1}$ (controls)	0.36	0.60***	0.64***	0.57*	0.224
<i>Stock fixed effects</i>					
Same day, r_{it}	1.39***	0.82***	0.46**	0.28**	0.0001***
Same day, r_{it} (controls)	1.40***	0.78***	0.44***	0.30**	0.0001***
Next day, $r_{i,t+1}$	0.16	0.46**	0.51**	0.51*	0.173
Next day, $r_{i,t+1}$ (controls)	0.43	0.64***	0.68***	0.58**	0.296
<i>Day fixed effects</i>					
Same day, r_{it}	0.94***	0.56***	0.37***	0.43***	0.004***
Same day, r_{it} (controls)	0.94***	0.58***	0.38***	0.45***	0.006***
Next day, $r_{i,t+1}$	0.00	0.16	0.33***	0.35***	0.050**
Next day, $r_{i,t+1}$ (controls)	0.02	0.19	0.35***	0.37***	0.033**
<i>Stock and day fixed effects</i>					
Same day, r_{it}	1.26***	0.74***	0.49***	0.60***	0.001***
Same day, r_{it} (controls)	1.25***	0.73***	0.50***	0.60***	0.002***
Next day, $r_{i,t+1}$	0.07	0.21	0.38***	0.44***	0.080*
Next day, $r_{i,t+1}$ (controls)	0.10	0.26	0.41***	0.46***	0.065*

Table F.9: Same-day and next-day slopes on narrative-predicted return, by quartile of $|V_{\text{cacophony}}|/(\alpha_i + \widehat{V})$.

Table entries present the slope on $\Lambda_i' F_{i,t} = \sum_k \lambda_{g(i),k} F_{k,t}$. Same-day rows use r_{it} as the dependent variable, checking same-day pass-through from narrative-implied return to realized return. Next-day rows use $r_{i,t+1}$, the next day's return of the same stock, checking for a momentum effect. Quartiles are equal-count bins of $|V_{\text{cacophony}}|/\widehat{V}_{\Gamma'X+\text{FEs}}$, where $|V_{\text{cacophony}}| = |\widehat{\gamma}_{H \times D}(H \times D)|$ estimates the amount of foregone trade volume attributable to cacophony, and $\Gamma'X + \text{FEs}$ is the model-predicted (explainable) volume, including stock FEs. Q1 is the lowest ratio and Q4 the highest. The four slope columns are separate regressions, with no fixed effects, stock fixed effects, day fixed effects, or both. The Q4–Q1 test stacks Q1 and Q4. Its fixed effects are quartile-specific, so the Q1 and Q4 slopes equal the slopes in those columns. The stacked regression is clustered on the original stock and the original day, so that any overlap enters the covariance. The Q4 – Q1 *p*-value is a one-sided normal *p*-value, consistent with the tested hypotheses: $\gamma_{\Lambda F, Q4}^{\text{next-day}} - \gamma_{\Lambda F, Q1}^{\text{next-day}} > 0$, and $\gamma_{\Lambda F, Q4}^{\text{next-day}} - \gamma_{\Lambda F, Q1}^{\text{next-day}} < 0$. Stars on that column use this one-sided *p*-value. Stars on the slope entries are two-sided tests that the slope equals zero: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All standard errors are clustered by stock and by calendar day. For the Q4–Q1 *p*-values in the rows without controls, the covariance is the Cameron–Gelbach–Miller sum of the stock, day, and stock-day pieces. Each piece is multiplied by $[G/(G-1)] \times [(n-1)/(n-k)]$ for G the number of clusters and k the number of regressors, excluding absorbed fixed effects.

	Pooled	Q1 low	Q2	Q3	Q4 high	Q4 – Q1	N
<i>Panel A. $V_{\text{cac}} /\widehat{V}_{\text{slopes}}$, control $r_{i,t+n-1}$</i>							
$r_{i,t+1}$	0.241* (0.149)	0.058 (0.191)	0.294* (0.185)	0.366*** (0.141)	0.559*** (0.191)	0.501** (0.273)	40,089
$r_{i,t+2}$	0.074 (0.103)	0.032 (0.118)	0.017 (0.108)	0.416*** (0.171)	0.154 (0.177)	0.121 (0.212)	39,606
$r_{i,t+3}$	-0.163 (0.152)	-0.200 (0.174)	-0.272 (0.195)	-0.105 (0.115)	-0.073 (0.151)	0.128 (0.224)	39,123
$r_{i,t+4}$	-0.392 (0.222)	-0.460 (0.263)	-0.233 (0.191)	-0.080 (0.109)	-0.346 (0.177)	0.114 (0.304)	38,640
<i>Panel B. $V_{\text{cac}} /\widehat{V}_{\text{slopes}}$, control $r_{i,t}$</i>							
$r_{i,t+1}$	0.241* (0.149)	0.058 (0.191)	0.294* (0.185)	0.366*** (0.141)	0.559*** (0.191)	0.501** (0.273)	40,089
$r_{i,t+2}$	0.077 (0.100)	0.057 (0.117)	-0.017 (0.132)	0.428*** (0.169)	0.206 (0.170)	0.149 (0.206)	39,606
$r_{i,t+3}$	-0.125 (0.142)	-0.157 (0.158)	-0.250 (0.205)	-0.075 (0.122)	-0.048 (0.147)	0.109 (0.209)	39,123
$r_{i,t+4}$	-0.315 (0.181)	-0.357 (0.229)	-0.192 (0.190)	-0.063 (0.109)	-0.325 (0.164)	0.032 (0.271)	38,640
<i>Panel C. $V_{\text{cac}} /(\alpha_i + \widehat{V}_{\text{slopes}})$, control $r_{i,t+n-1}$</i>							
$r_{i,t+1}$	0.241* (0.149)	0.097 (0.196)	0.256* (0.176)	0.413*** (0.135)	0.456*** (0.164)	0.360* (0.242)	40,089
$r_{i,t+2}$	0.074 (0.103)	0.074 (0.112)	0.006 (0.120)	0.169* (0.127)	0.200* (0.135)	0.127 (0.165)	39,606
$r_{i,t+3}$	-0.163 (0.152)	-0.134 (0.138)	-0.321 (0.225)	-0.172 (0.116)	-0.067 (0.123)	0.067 (0.178)	39,123
$r_{i,t+4}$	-0.392 (0.222)	-0.438 (0.259)	-0.329 (0.259)	-0.175 (0.123)	-0.271 (0.136)	0.167 (0.279)	38,640
<i>Panel D. $V_{\text{cac}} /(\alpha_i + \widehat{V}_{\text{slopes}})$, control $r_{i,t}$</i>							
$r_{i,t+1}$	0.241* (0.149)	0.097 (0.196)	0.256* (0.176)	0.413*** (0.135)	0.456*** (0.164)	0.360* (0.242)	40,089
$r_{i,t+2}$	0.077 (0.100)	0.100 (0.109)	-0.016 (0.137)	0.164* (0.120)	0.247** (0.132)	0.147 (0.161)	39,606
$r_{i,t+3}$	-0.125 (0.142)	-0.103 (0.122)	-0.278 (0.230)	-0.140 (0.117)	-0.040 (0.125)	0.063 (0.169)	39,123
$r_{i,t+4}$	-0.315 (0.181)	-0.354 (0.217)	-0.260 (0.246)	-0.148 (0.123)	-0.255 (0.125)	0.099 (0.241)	38,640

One-sided tests of a positive coefficient. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.10: Narrative slope on future returns at various horizons, by bins of $\widehat{V}_{\text{cacophony}}/\widehat{V}$

The dependent variable is $r_{i,t+n}$ for $n = 1, 2, 3, 4$. Each cell is the coefficient on $\lambda' f_t$ from a horse race of that return on the narrative prediction and on a lagged return. Panels A and B control for $r_{i,t+n-1}$. Panels C and D control for $r_{i,t}$. At $n = 1$ the two controls are the same return, so the two panels are the same regression. Pooled uses every stock-day. Q1 through Q4 are separate regressions on the stock-days in that quartile of $|V_{\text{cac}}|/\widehat{V}_{\text{slopes}}$. The ratio is used only to sort stock-days into quartiles. Every regression includes stock and day fixed effects, $H \times D$, D , H , and the relative bidask spread. Quartiles are cut on the $n = 1$ sample and held fixed at longer horizons. $|V_{\text{cac}}| = |\widehat{\beta}_{H \times D}(H \times D)|$ is the cacophony component from a volume regression with stock fixed effects. $\widehat{V}_{\text{slopes}}$ is fitted volume from the slope coefficients in that regression, leaving out the stock effect. Q4 – Q1 is the difference in the narrative slope from a stacked regression of Q1 and Q4, with quartile-specific stock and day fixed effects, clustered by the original stock and day, with a one-sided test p-value reported. N is the number of stock-days in the pooled regression. Parentheses are standard errors clustered by stock and by day.

	Same day, r_{it}			Next day, $r_{i,t+1}$				
	No FE	Stock	Day	Both	No FE	Stock	Day	Both
<i>No controls</i>								
Two-way cluster, industry and day	<0.001***	<0.001***	0.001***	<0.001***	0.157	0.180	0.024**	0.023**
Two-way cluster, industry and day, wild bootstrap	0.007***	0.005***	0.008***	0.012**	0.320	0.349	0.056*	0.084*
One-way cluster, industry, wild bootstrap	0.001***	0.001***	0.006***	0.011**	0.030**	0.034**	0.001***	0.003***
Two-way cluster, stock and day	<0.001***	<0.001***	0.002***	0.001***	0.180	0.200	0.036**	0.038**
Two-way cluster, stock and day, date wild bootstrap	0.001***	0.001***	0.002***	0.001***	0.196	0.219	0.083*	0.082*
One-way cluster, stock	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
Driscoll–Kraay, 3-day lag	<0.001***	<0.001***	0.001***	<0.001***	0.107	0.129	0.053*	0.050*
Driscoll–Kraay, 5-day lag	<0.001***	<0.001***	0.001***	<0.001***	0.087*	0.107	0.066*	0.059*
Moving-block bootstrap, 5-day blocks	0.008***	0.009***	0.004***	0.001***	0.106	0.137	0.100	0.106
<i>With controls</i>								
Two-way cluster, industry and day	<0.001***	<0.001***	0.002***	<0.001***	0.232	0.308	0.011**	0.020**
Two-way cluster, industry and day, wild bootstrap	0.010**	0.008***	0.007***	0.016**	0.446	0.493	0.040**	0.090*
One-way cluster, industry, wild bootstrap	0.001***	0.001***	0.009***	0.008***	0.080*	0.157	0.003***	0.008***
Two-way cluster, stock and day	<0.001***	<0.001***	0.004***	0.002***	0.259	0.325	0.020**	0.030**
Two-way cluster, stock and day, date wild bootstrap	0.001***	0.001***	0.003***	0.002***	0.275	0.340	0.050**	0.062*
One-way cluster, stock	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	0.001***	<0.001***	<0.001***
Driscoll–Kraay, 3-day lag	<0.001***	<0.001***	0.002***	<0.001***	0.178	0.262	0.023**	0.026**
Driscoll–Kraay, 5-day lag	<0.001***	<0.001***	0.001***	<0.001***	0.157	0.245	0.032**	0.031**
Moving-block bootstrap, 5-day blocks	0.008***	0.007***	0.005***	0.001***	0.187	0.280	0.059*	0.088*

Table F.11: Alternative clustering: same-day and next-day pricing of narratives, by $|\hat{V}_{\text{cacophony}}|/\hat{V}$ quartile

Every cell is a one-sided p-value on the Q4Q1 slope gap (same day: Q4 below Q1; next day: Q4 above Q1), with 1,999 bootstrap draws. The stock-and-day row matches the saved slope tables. This table uses the $\hat{V}_{\text{ac}}/\hat{V}$ (slopes-only denominator) quartile sorting, and reports results for the stock and day fixed effects with controls.

	Same day, r_{it}			Next day, $r_{i,t+1}$				
	No FE	Stock	Day	Both	No FE	Stock	Day	Both
<i>No controls</i>								
Two-way cluster, industry and day	<0.001***	<0.001***	0.005***	<0.001***	0.113	0.140	0.041**	0.065*
Two-way cluster, industry and day, wild bootstrap	0.014**	0.009***	0.015**	0.012**	0.480	0.471	0.068*	0.143
One-way cluster, industry, wild bootstrap	0.001***	0.001***	0.007***	0.004***	0.010***	0.009***	0.007***	0.039**
Two-way cluster, stock and day	<0.001***	<0.001***	0.004***	0.001***	0.148	0.173	0.050**	0.080*
Two-way cluster, stock and day, date wild bootstrap	0.001***	0.001***	0.002***	0.001***	0.165	0.201	0.080*	0.114
One-way cluster, stock	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
Driscoll–Kraay, 3-day lag	<0.001***	<0.001***	0.001***	<0.001***	0.074*	0.094*	0.066*	0.092*
Driscoll–Kraay, 5-day lag	<0.001***	<0.001***	<0.001***	<0.001***	0.046**	0.062*	0.074*	0.093*
Moving-block bootstrap, 5-day blocks	0.005***	0.003***	0.001***	0.001***	0.075*	0.099*	0.090*	0.136
<i>With controls</i>								
Two-way cluster, industry and day	<0.001***	<0.001***	0.006***	0.001***	0.184	0.269	0.026**	0.058*
Two-way cluster, industry and day, wild bootstrap	0.007***	0.009***	0.016**	0.013**	0.463	0.537	0.085*	0.144
One-way cluster, industry, wild bootstrap	0.001***	0.001***	0.004***	0.004***	0.032**	0.077*	0.007***	0.049**
Two-way cluster, stock and day	<0.001***	<0.001***	0.006***	0.002***	0.224	0.296	0.033**	0.065*
Two-way cluster, stock and day, date wild bootstrap	0.001***	0.001***	0.003***	0.001***	0.232	0.302	0.060*	0.086*
One-way cluster, stock	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	0.002***	<0.001***	<0.001***
Driscoll–Kraay, 3-day lag	<0.001***	<0.001***	0.002***	<0.001***	0.139	0.221	0.034**	0.055*
Driscoll–Kraay, 5-day lag	<0.001***	<0.001***	<0.001***	<0.001***	0.096*	0.177	0.042**	0.052*
Moving-block bootstrap, 5-day blocks	0.007***	0.009***	0.002***	0.001***	0.154	0.256	0.067*	0.103

Table F.12: Alternative clustering: same-day and next-day pricing of narratives, by $|\hat{V}_{\text{cacophony}}|/\alpha + \hat{V}$ quartile

Every cell is a one-sided p-value on the Q4Q1 slope gap (same day: Q4 below Q1; next day: Q4 above Q1), with 1,999 bootstrap draws. The stock-and-day row matches the saved slope tables. This table uses the $\hat{V}_{\text{cac}}/\alpha + \hat{V}$ (denominator includes FEs) quartile sorting, and reports results for the stock and day fixed effects with controls.

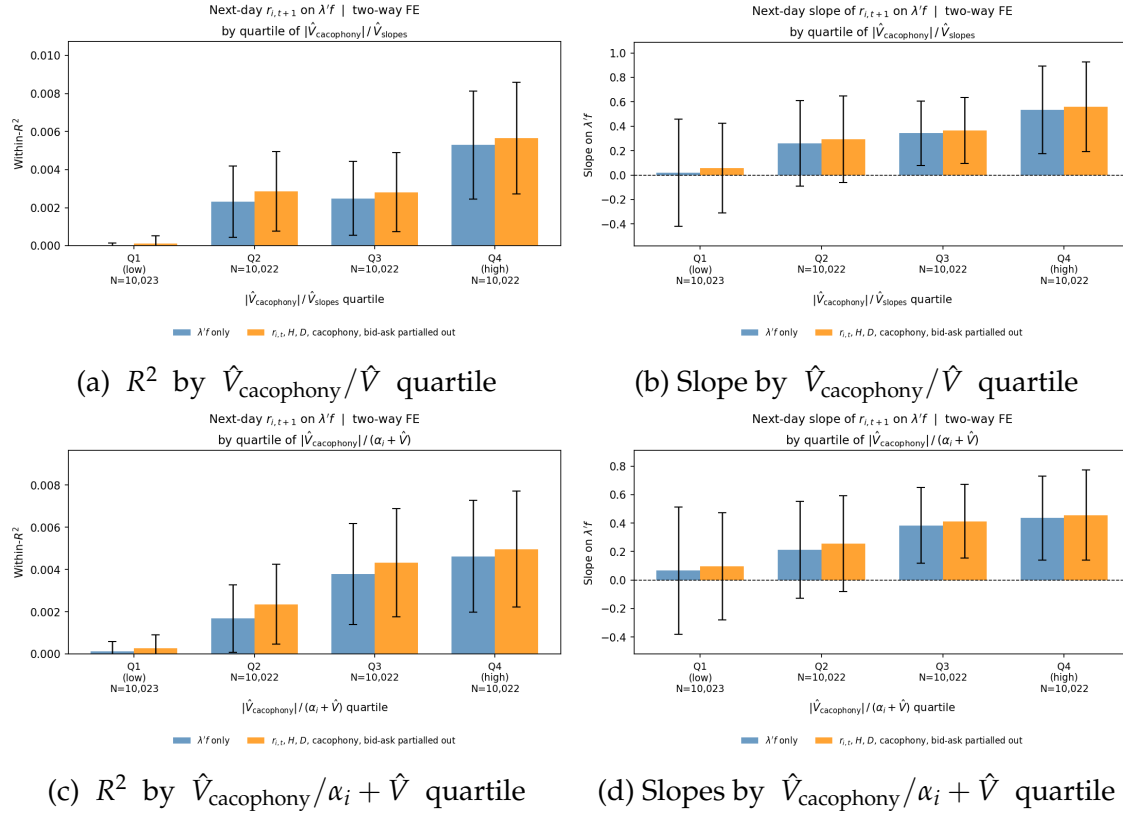


Figure F.5: R^2 and slopes of forecasting regressions by quartile of cacophony-suppressed volume

The left display the R^2 from separate regression of the same-day return inside the corresponding quartile of $|\hat{V}_{\text{cacophony}}|/\hat{V}$ (without and with stock fixed effects included in the denominator, on the left and right, respectively). Right panels show the corresponding slopes. The numerator of the quartile-sorting variable is the cacophony piece of fitted log volume, $|\hat{V}_{\text{cacophony}}| = |\hat{\gamma}_{H \times D}(H_{it} \times D_{it})|$, and $\hat{V}$ is the slope component of that fit. Q1 is the lowest cacophony-suppressed volume ratio and Q4 the highest. Each quartile has 10,143 stock-days. 95% confidence intervals for the R^2 are shown ($\hat{R}^2 \pm 1.95 \times 2\sqrt{\hat{R}^2(1 - \hat{R}^2)^2/N}$). Forecasting regressions explain $r_{i,t+1}$ by $(\Delta F)_{i,t}$. Blue bars show the bivariate regressions; orange bars partial out narrative dispersion, directional disagreement, cacophony, the bid-ask spread, and the realized (date- t) return (so that the R^2 is a partial R^2).

G What are the measures of disagreement, and are they distinct?

It is natural to wonder whether τ, H, D and $H \times D$ isolate different properties of narrative exposure, given that they're constructed from the same exposure weights. In Tables G.1 and G.2, I verify their separability empirically.

Panel A. Spearman correlations			
	$\rho(H, D)$	$\rho(H, \tau)$	$\rho(\tau, D)$
Raw	0.226	0.093	0.212
Within stock	0.244	0.132	0.267
Within date	0.211	-0.231	0.009
Stock and date	0.247	-0.157	0.121

Panel A2. Pearson correlations			
	$\rho(H, D)$	$\rho(H, \tau)$	$\rho(\tau, D)$
Raw	0.375	0.101	0.182
Within stock	0.382	0.129	0.199
Within date	0.274	-0.149	0.039
Stock and date	0.282	-0.103	0.105

Panel B. D within H quintiles			
H quintile	Mean D	SD(D)	N
Q1	0.6961	0.2154	8,126
Q2	0.7716	0.1677	8,140
Q3	0.8285	0.1417	8,080
Q4	0.8219	0.1398	8,114
Q5	0.8321	0.1108	8,112

Panel B2. τ within H quintiles			
H quintile	Mean τ	SD(τ)	N
Q1	0.0288	0.0288	8,126
Q2	0.0345	0.0391	8,140
Q3	0.0412	0.0472	8,080
Q4	0.0414	0.0491	8,114
Q5	0.0382	0.0391	8,112

Panel B3. D within τ quintiles			
τ quintile	Mean D	SD(D)	N
Q1	0.7516	0.2070	8,123
Q2	0.7571	0.1732	8,110
Q3	0.7584	0.1579	8,112
Q4	0.8226	0.1431	8,119
Q5	0.8602	0.1098	8,108

Panels A and A2 are pairwise correlations of the stock-day panel. Panel A is Spearman. Panel A2 is Pearson. Within stock, within date, and stock and date are one-pass demeaned series.

Table G.1: Correlations: τ, H, D

Panel A. $H \times D$ within D Quartiles

Bin	Range	N	Mean D	SD(D)	Mean $H \times D$	SD($H \times D$)	$\rho(H \times D, D)$	
							Spearman	Pearson
Q1	0.09–0.70	10,169	0.553	0.123	1.043	0.285	0.857	0.930
Q2	0.70–0.83	10,118	0.768	0.036	1.508	0.160	0.465	0.468
Q3	0.83–0.93	10,156	0.879	0.029	1.764	0.153	0.408	0.404
Q4	0.93–1.00	10,129	0.961	0.021	1.907	0.150	0.237	0.254

Panel B. $H \times D$ within D Terciles

Bin	Range	N	Mean D	SD(D)	Mean $H \times D$	SD($H \times D$)	$\rho(H \times D, D)$	
							Spearman	Pearson
T1	0.09–0.75	13,534	0.596	0.130	1.135	0.303	0.872	0.927
T2	0.75–0.90	13,524	0.826	0.043	1.642	0.171	0.550	0.546
T3	0.90–1.00	13,514	0.949	0.029	1.889	0.151	0.309	0.312

Panel C. $H \times D$ within H Quartiles

Bin	Range	N	Mean H	SD(H)	Mean $H \times D$	SD($H \times D$)	$\rho(H \times D, H)$	
							Spearman	Pearson
Q1	0.77–1.85	10,155	1.699	0.148	1.228	0.394	0.485	0.637
Q2	1.85–1.98	10,133	1.912	0.037	1.507	0.312	0.296	0.293
Q3	1.98–2.09	10,161	2.035	0.036	1.695	0.281	0.140	0.123
Q4	2.09–2.42	10,123	2.170	0.060	1.791	0.265	0.252	0.259

Panel D. $H \times D$ within H Terciles

Bin	Range	N	Mean H	SD(H)	Mean $H \times D$	SD($H \times D$)	$\rho(H \times D, H)$	
							Spearman	Pearson
T1	0.77–1.89	13,560	1.742	0.148	1.274	0.385	0.424	0.594
T2	1.89–2.05	13,520	1.974	0.047	1.607	0.296	0.201	0.172
T3	2.05–2.42	13,492	2.146	0.066	1.786	0.259	0.174	0.198

Panel E. $H \times D$ within τ Quartiles

Bin	Range	N	Mean τ	SD(τ)	Mean $H \times D$	SD($H \times D$)	$\rho(H \times D, \tau)$	
							Spearman	Pearson
Q1	0.0015–0.0148	10,186	0.009	0.003	1.474	0.450	0.064	0.193
Q2	0.0148–0.0228	10,143	0.019	0.002	1.477	0.372	0.021	0.033
Q3	0.0229–0.0383	10,131	0.029	0.004	1.556	0.357	0.087	0.069
Q4	0.0383–0.3075	10,112	0.090	0.054	1.716	0.279	-0.077	-0.060

Panel F. $H \times D$ within τ Terciles

Bin	Range	N	Mean τ	SD(τ)	Mean $H \times D$	SD($H \times D$)	$\rho(H \times D, \tau)$	
							Spearman	Pearson
T1	0.0015–0.0173	13,527	0.011	0.004	1.469	0.436	-0.002	0.104
T2	0.0173–0.0308	13,539	0.023	0.004	1.524	0.360	0.133	0.141
T3	0.0308–0.3075	13,506	0.076	0.052	1.673	0.312	0.123	0.068

Terciles and quartiles are equal-frequency bins of the conditioning variable. The correlation is of $H \times D$ with that same variable, computed inside the bin. Spearman is the rank correlation and Pearson is the linear correlation.

Table G.2: Correlations: $H \times D$ with the others

H Placebo Tests: Are pricing results driven by volume or cacophony?

It is well-known that trading and prices are related. Since the cacophony share is negatively related to volume by construction, this invites a natural question: what if all effects are driven not by cacophony-attributable share of volume lost, but simply realized volume? More formally:

Hypothesis 1. Null hypothesis: The relation between returns and $\Lambda'F$ depends only on how much trading takes place. The cacophony share matters only because it is a proxy for low-volume stock-days.

It is important to bear in mind that higher volume corresponds, intuitively, to the case of low cacophony-suppressed volume share, so the sorting and the direction of results go in the opposite directions.

The analysis proceeds in the following three robustness tests:

1. *Holding realized volume fixed, does $\Lambda'F$ explain less of returns when the cacophony share is high?* Yes: within realized-volume deciles, the partial R^2 of same-day returns on $\Lambda'F$ is lower by -0.251 ($p = 0.001$) in the highest-share quartile than in the lowest. The gap survives, though smaller (-0.105 , $p = 0.008$), when the size of the narrative signal is held fixed instead.
2. *Can differences in volume alone reproduce how the slope on $\Lambda'F$ falls with the cacophony share?* No: realized volume and the cacophony share account for 60-70% of the share gradient, and both leave unexplained a portion of what the other explains.
3. *When $\Lambda'F$ is interacted with both the cacophony share and realized volume in one pooled regression, does the share interaction survive?* Yes: with stock and day fixed effects, it is -0.463^{***} with a linear volume control and -0.551^{***} when the loading on $\Lambda'F$ varies freely across volume deciles.

H.1 Measures

Volume stage. As in the main analysis, I regress log turnover on narrative dispersion H , directional disagreement D , their interaction $H \times D$ (cacophony), the aggregate narrative-implied price-pressure of tariffs τ , the absolute return, lagged log turnover, log article counts, and the commodity tariff factor return, with stock fixed effects. The within- R^2 is 0.436 and $\hat{\beta}_{H \times D} = -0.608$. From this regression I build:

- $\hat{V}$: the fitted value $\Gamma'X$, leaving out the stock effect.
- $\alpha_i + \hat{V}$: the fitted level, including the intercept and the stock effect.
- $|\hat{V}_{\text{cac}}| = |\hat{\beta}_{H \times D}(H \times D)_{it}|$: the volume that cacophony suppresses.
- The cacophony-suppressed share of volume (hence forth: cacophony share, for brevity), $|\hat{V}_{\text{cac}}|/\hat{V}$, and its level version, $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$.

H.2 Baseline: Single Sorts by Volume and by Cacophony Share

Table H.1 shows that both cacophony shares are negatively correlated with realized volume (rank correlations of -0.50 and -0.62). The numerator alone, $|\hat{V}_{\text{cac}}|$, is essentially uncorrelated with any volume measure. A falling pattern across cacophony share quartiles is therefore partly what the volume-only null would generate on its own.

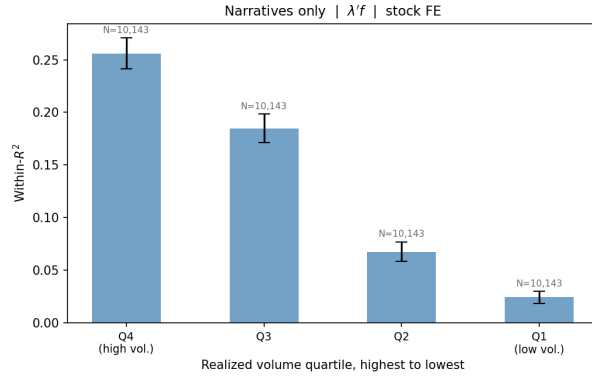
Table H.1: Rank correlations

	$ \hat{V}_{\text{cac}} /\hat{V}$	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	$ \hat{V}_{\text{cac}} $	$\hat{V}$	$\alpha_i + \hat{V}$	log turnover
$ \hat{V}_{\text{cac}} /\hat{V}$	1.00	0.96	0.76	-0.60	-0.57	-0.50
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$		1.00	0.66	-0.67	-0.71	-0.62
$ \hat{V}_{\text{cac}} $			1.00	-0.02	-0.02	-0.02
$\hat{V}$				1.00	0.95	0.83
$\alpha_i + \hat{V}$					1.00	0.87
log turnover						1.00

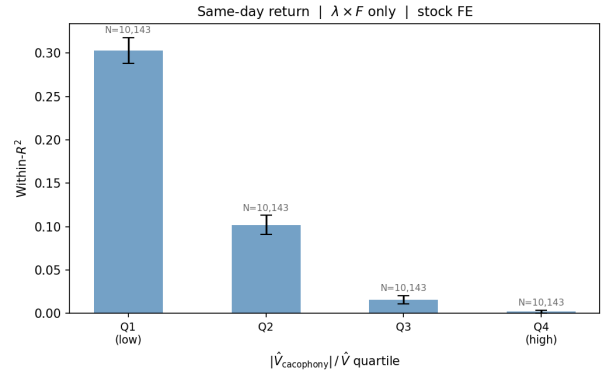
Spearman rank correlations across 40,572 stock-days. Realized volume is log turnover.

Indeed, Figure H.1 contrasts the two single sorts for the regression of same-day returns on $\Lambda'F$ alone, with stock fixed effects. Sorted by realized volume, the within- R^2 rises from 0.024 to 0.067 , 0.185 , and 0.256 . Sorted by the cacophony share, it falls from 0.303 to 0.102 , 0.016 , and 0.002 . The CAPM benchmark (stock intercepts and stock-specific market betas, adjusted R^2) shows a similar directional pattern, but with non-monotonicity and weaker decline: 0.50 , 0.50 , 0.39 , 0.37 by realized volume, and 0.55 , 0.40 , 0.31 , 0.29 by cacophony share.

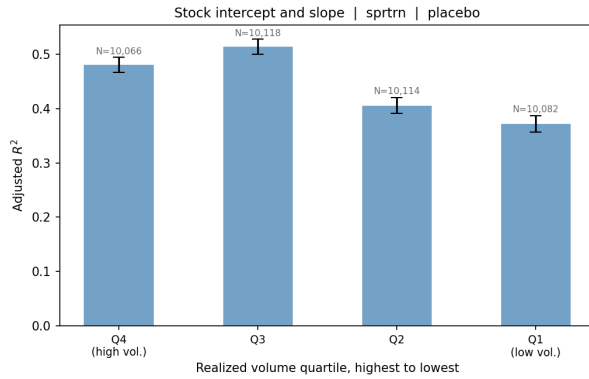
These patterns are broadly what one would expect under either hypothesis (except the non-monotonicity for CAPM), and they cannot by themselves distinguish the two. Every test below is designed to separate the cacophony share from volume.



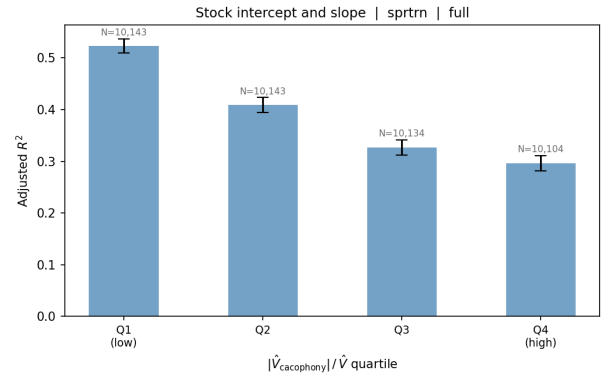
(a) Narrative factors, by realized volume quartile



(b) Narrative factors, by $|\hat{V}_{cac}|/\hat{V}$ quartile



(c) CAPM, by realized volume quartile



(d) CAPM, by $|\hat{V}_{cac}|/\hat{V}$ quartile

Figure H.1: R^2 of same-day returns, single sorts: narrative factors and CAPM

Panels (a) and (b): within- R^2 of r_{it} on $\Lambda'F$ with stock fixed effects inside each quartile. Panels (c) and (d): adjusted R^2 of r_{it} on the CRSP market return with stock-specific intercepts and betas inside each quartile. Panels (a) and (c) are the realized-volume placebo; panels (b) and (d) sort on the cacophony share. Realized-volume axes run from the highest-volume quartile (Q4, left) to the lowest (Q1, right), so that in every panel expected market efficiency falls from left to right.

H.3 Test 1: Does the Cacophony Share Matter Holding Realized Volume Fixed?

Design. I split stock-days into realized-volume quartiles and, separately, deciles. Within each volume bin I sort stock-days into quartiles of the cacophony share and compare the lowest-share quartile (C1) with the highest-share quartile (C4). Under the volume-only null, $\Lambda'F$ should fit returns equally well on stock-days in the same volume bin, regardless of their cacophony share. I test this on the R^2 gap $R_{C4}^2 - R_{C1}^2$ from a regression of returns on $\Lambda'F$ (Hypothesis 2 of the main paper). Whether a high share also lowers pass-through, the slope on $\Lambda'F$, is the subject of Tests 2 and 3.

Inference. Standard errors come from a bootstrap over trading days (999 draws). Each draw resamples the 84 trading days with replacement and keeps every stock-day on a drawn day, which preserves the strong cross-sectional correlation of returns within a day. Cell assignments are held fixed. The alternative is a negative gap (C4 below C1), and all p -values in this section are one-sided.

R^2 results. Table H.2 reports the mean R^2 gap across bins. With volume deciles, stock fixed effects, and controls, the mean gap in partial R^2 is -0.251 for $|\hat{V}_{\text{cac}}|/\hat{V}$ ($p = 0.001$) and -0.177 for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$ ($p = 0.005$). Table H.3 and Figure H.2 show the decile detail. The low cacophony-share R^2 climbs with volume, from 0.06 in the lowest decile to as much as 0.47 in the top deciles. The high cacophony-share R^2 stays between 0.00 and 0.02 in every decile. Essentially, in the low realized-volume deciles, volume is already low, and there is little margin for cacophony to suppress trade further, so the difference between high cacophony-share and low cacophony-share observations vanishes. In the high realized volume deciles, by contrast, there is ample room for cacophony-share to further suppress trade. Results without fixed effects, and without controls, are nearly identical.

CAPM likewise follows the same pattern. With volume deciles, stock fixed effects, and controls, the mean CAPM R^2 gap is -0.244 for $|\hat{V}_{\text{cac}}|/\hat{V}$ ($p = 0.006$) and -0.150 for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$ ($p = 0.043$).²⁰ Holding realized volume fixed, high-share stock-days are less well explained by the market as well as by narratives, so the loss of fit is not specific to the narrative factors.

The R^2 gap rejects the volume-only null as realized volume does not determine how well $\Lambda'F$ fits.

²⁰Confirming again that pure cacophony, without scaling by volume, is not the relevant variable: there is no CAPM R^2 gap ($+0.053$, $p = 0.737$).

H.3.1 Holding the size of the narrative signal fixed.

The R^2 pattern could also be a quasi-mechanical feature of high cacophony-share stock-days corresponding exactly to stock-days with a small narrative signal. For a given slope, the R^2 of a regression on $\Lambda'F$ rises with the variance of $\Lambda'F$ relative to the noise in returns, so an observation with a smaller signal fits worse even if prices absorb the signal just as fully. Table H.4 shows that the concern applies here. Both cacophony shares are negatively correlated with the size of the signal, $|\Lambda'F|$: the rank correlations are -0.56 for $|\hat{V}_{\text{cac}}|/\hat{V}$ and -0.47 for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$, and the Pearson correlations are -0.39 and -0.31 . I therefore repeat the narrative R^2 test with quartiles of $|\Lambda'F|$ in place of the realized-volume bins. Inside each $|\Lambda'F|$ quartile I sort stock-days into quartiles of the cacophony share and compare C1 with C4. Cells, specifications, and the bootstrap are as above, and each cell holds about 2,536 stock-days. Because the bins are defined by the narrative signal, I run this test for $\Lambda'F$ only, without the CAPM benchmark. If the gap reflected only smaller signals on high-share stock-days, it would disappear once the size of the signal is held roughly fixed.

Results with the signal held fixed. Table H.5 and Figure H.3 report the results. With stock fixed effects and controls, the mean gap in partial R^2 across $|\Lambda'F|$ quartiles is -0.105 for $|\hat{V}_{\text{cac}}|/\hat{V}$ ($p = 0.008$) and -0.079 for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$ ($p = 0.017$).

In fact, the primary result is concentrated in the highest $|\Lambda'F|$ quartiles. In the top quartile, the only one in which $\Lambda'F$ is large enough to meaningfully explain returns, the partial R^2 is 0.473 in the lowest-share quartile and 0.058 in the highest ($p = 0.008$); for the level share it is 0.422 against 0.104 ($p = 0.015$). Within this top quartile the share is only weakly related to the size of the signal. (The rank correlation between $|\hat{V}_{\text{cac}}|/\hat{V}$ and $|\Lambda'F|$ is -0.10 , compared to -0.56 in the full sample, and the standard deviation of $\Lambda'F$ is 0.020 in C1 and 0.017 in C4).

These results are more sensitive to the controls than those within realized-volume bins. Without controls, with stock fixed effects, the mean gap is -0.073 for $|\hat{V}_{\text{cac}}|/\hat{V}$ ($p = 0.075$) and -0.048 for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$ ($p = 0.137$).

The loss of fit on high-share stock-days is therefore not only a by-product of smaller narrative signals on those days. Holding the size of the signal roughly fixed, high-share stock-days still fit $\Lambda'F$ less well, and the difference is concentrated among the stock-days with the largest narrative signals. As with the realized-volume bins, the R^2 gap speaks to fit rather than to pass-through.

Table H.2: Loss of R^2 within realized-volume bins: mean gap across bins

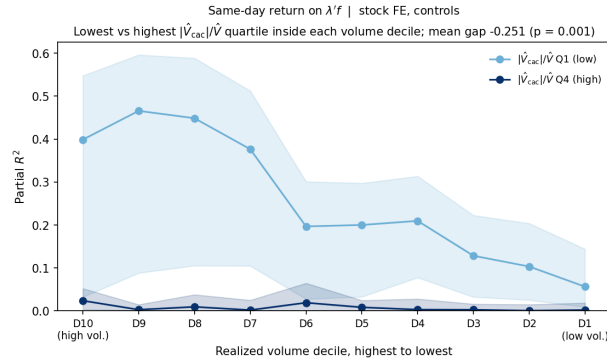
Regressor	Inner sort Controls	No FE		Stock FE	
		No	Yes	No	Yes
<i>Panel A: Realized-volume deciles</i>					
Narrative factors	$ \hat{V}_{\text{cac}} /\hat{V}$	−0.244*** (0.002)	−0.249*** (0.001)	−0.244*** (0.003)	−0.251*** (0.001)
	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	−0.172** (0.013)	−0.180*** (0.008)	−0.163*** (0.010)	−0.177*** (0.005)
	$ \hat{V}_{\text{cac}} $	−0.071 (0.126)	−0.082* (0.071)	−0.084** (0.043)	−0.097** (0.017)
CAPM	$ \hat{V}_{\text{cac}} /\hat{V}$	−0.280*** (0.002)	−0.278*** (0.003)	−0.246*** (0.006)	−0.244*** (0.006)
	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	−0.188** (0.025)	−0.183** (0.026)	−0.153** (0.040)	−0.150** (0.043)
	$ \hat{V}_{\text{cac}} $	+0.062 (0.740)	+0.062 (0.741)	+0.052 (0.731)	+0.053 (0.737)
<i>Panel B: Realized-volume quartiles</i>					
Narrative factors	$ \hat{V}_{\text{cac}} /\hat{V}$	−0.246*** (0.003)	−0.249*** (0.002)	−0.261*** (0.002)	−0.264*** (0.001)
	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	−0.172** (0.015)	−0.180** (0.010)	−0.192*** (0.008)	−0.203*** (0.005)
	$ \hat{V}_{\text{cac}} $	−0.077* (0.093)	−0.085* (0.056)	−0.089** (0.039)	−0.100** (0.017)
CAPM	$ \hat{V}_{\text{cac}} /\hat{V}$	−0.269*** (0.005)	−0.267*** (0.005)	−0.261*** (0.005)	−0.256*** (0.006)
	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	−0.173** (0.037)	−0.170** (0.039)	−0.171** (0.034)	−0.169** (0.036)
	$ \hat{V}_{\text{cac}} $	+0.049 (0.697)	+0.048 (0.694)	+0.038 (0.665)	+0.037 (0.663)

Entries are the equal-weighted mean across volume bins of $R_{C4}^2 - R_{C1}^2$, where C1 and C4 are the lowest and highest quartiles of the inner sort variable inside each realized-volume bin. The same-day return r_{it} is regressed on $\Delta'F$ (narrative factors) or on $\hat{\beta}_i r_{m,t}$ (CAPM). Fixed effects are specific to each cell. With controls (H , D , $H \times D$, bid-ask spread), the entry is the gap in the partial R^2 of the regressor. One-sided p -values in parentheses ($H_1: \text{gap} < 0$) from a 999-draw bootstrap over trading days. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

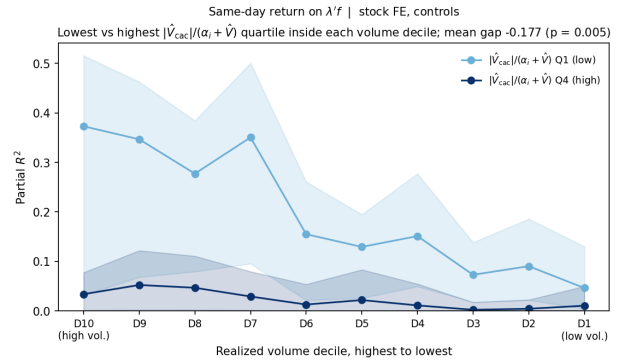
Table H.3: Loss of R^2 within realized-volume deciles, same-day returns, stock FE and controls: narrative factors and CAPM

Volume decile	Inner sort: $ \hat{V}_{\text{cac}} /\hat{V}$				Inner sort: $ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$			
	R^2_{C1}	R^2_{C4}	Gap	p	R^2_{C1}	R^2_{C4}	Gap	p
<i>Panel A: Narrative factors, $\Lambda'F$</i>								
D1	0.056	0.002	−0.054	0.100	0.046	0.010	−0.036	0.190
D2	0.103	0.000	−0.103	0.034	0.090	0.004	−0.086	0.042
D3	0.128	0.002	−0.126	0.016	0.073	0.002	−0.071	0.026
D4	0.209	0.003	−0.207	0.003	0.151	0.011	−0.140	0.036
D5	0.200	0.008	−0.192	0.012	0.129	0.022	−0.107	0.053
D6	0.196	0.019	−0.178	0.024	0.155	0.013	−0.142	0.035
D7	0.376	0.001	−0.375	0.002	0.350	0.029	−0.321	0.010
D8	0.449	0.009	−0.440	0.002	0.277	0.047	−0.231	0.008
D9	0.466	0.002	−0.464	0.002	0.346	0.052	−0.294	0.015
D10	0.399	0.023	−0.376	0.010	0.373	0.034	−0.339	0.011
Mean	0.258	0.007	−0.251	0.001	0.199	0.022	−0.177	0.005
<i>Panel B: CAPM, $\hat{\beta}_i r_{m,t}$</i>								
D1	0.290	0.226	−0.064	0.199	0.275	0.264	−0.010	0.450
D2	0.333	0.287	−0.046	0.297	0.344	0.345	+0.001	0.506
D3	0.352	0.292	−0.060	0.257	0.298	0.328	+0.030	0.624
D4	0.485	0.279	−0.206	0.038	0.364	0.249	−0.115	0.127
D5	0.410	0.196	−0.214	0.017	0.384	0.227	−0.157	0.063
D6	0.421	0.258	−0.162	0.090	0.391	0.281	−0.110	0.178
D7	0.598	0.212	−0.385	0.004	0.557	0.279	−0.278	0.033
D8	0.676	0.235	−0.440	0.002	0.497	0.277	−0.220	0.024
D9	0.632	0.187	−0.445	0.003	0.543	0.277	−0.266	0.042
D10	0.557	0.143	−0.414	0.010	0.545	0.175	−0.370	0.012
Mean	0.475	0.232	−0.244	0.006	0.420	0.270	−0.150	0.043

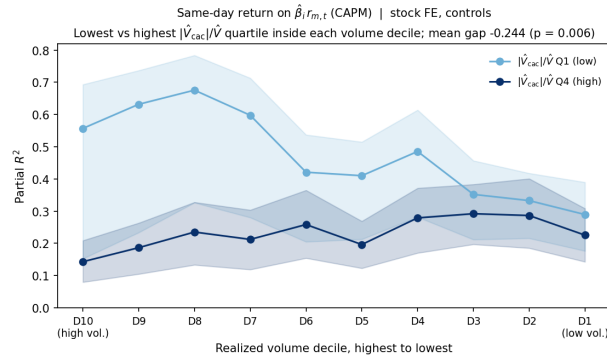
Partial R^2 of the regressor, after the controls and stock fixed effects, in the lowest (C1) and highest (C4) cacophony-share quartile inside each realized-volume decile. Panel A regresses r_{it} on $\Lambda'F$; Panel B regresses r_{it} on the CAPM fitted return $\hat{\beta}_i r_{m,t}$, with identical cells. One-sided p -values ($H_1: \text{gap} < 0$) from a 999-draw bootstrap over trading days.



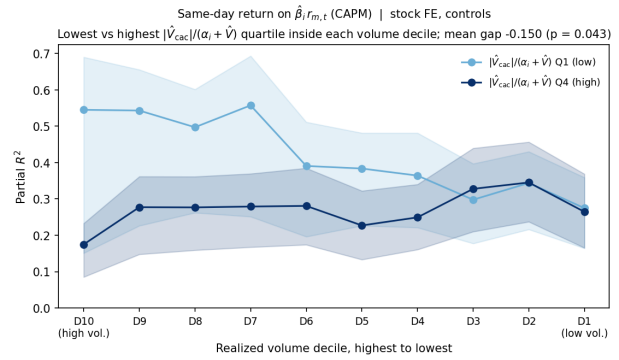
(a) Narrative factors, $|\hat{V}_{\text{cac}}|/\hat{V}$



(b) Narrative factors, $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$



(c) CAPM, $|\hat{V}_{\text{cac}}|/\hat{V}$



(d) CAPM, $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$

Figure H.2: Partial R^2 in the lowest and highest cacophony-share quartile inside each realized-volume decile

Same-day returns, stock fixed effects and controls. Shaded bands are 90% bootstrap intervals over trading days. The panel titles report the mean gap across deciles and its one-sided p -value. The horizontal axis runs from the highest realized-volume decile (D10, left) to the lowest (D1, right).

Table H.4: Correlations of the cacophony shares with the size of the narrative signal

	$ \hat{V}_{\text{cac}} /\hat{V}$	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	$ \Lambda'F $
<i>Panel A: Pearson correlations</i>			
$ \hat{V}_{\text{cac}} /\hat{V}$	1.00	0.95	-0.39
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$		1.00	-0.31
$ \Lambda'F $			1.00
<i>Panel B: Spearman rank correlations</i>			
$ \hat{V}_{\text{cac}} /\hat{V}$	1.00	0.96	-0.56
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$		1.00	-0.47
$ \Lambda'F $			1.00

Pearson (Panel A) and Spearman rank (Panel B) correlations across 40,572 stock-days. $|\Lambda'F|$ is the absolute value of the narrative-implied return.

Table H.5: Loss of R^2 within quartiles of $|\Lambda'F|$, same-day returns on narrative factors

	Inner sort: $ \hat{V}_{cac} /\hat{V}$				Inner sort: $ \hat{V}_{cac} /(\alpha_i + \hat{V})$			
	R^2_{C1}	R^2_{C4}	Gap	p	R^2_{C1}	R^2_{C4}	Gap	p
<i>Panel A: By $\Lambda'F$ quartile, stock FE, controls</i>								
Q1	0.000	0.007	+0.006	0.708	0.001	0.010	+0.009	0.793
Q2	0.013	0.004	-0.010	0.327	0.008	0.002	-0.006	0.368
Q3	0.000	0.000	-0.000	0.489	0.000	0.000	-0.000	0.489
Q4	0.473	0.058	-0.415	0.008	0.422	0.104	-0.317	0.015
Mean	0.122	0.017	-0.105	0.008	0.108	0.029	-0.079	0.017
<i>Panel B: Mean across $\Lambda'F$ quartiles, other specifications</i>								
No FE	0.107	0.039	-0.068	0.056	0.095	0.052	-0.042	0.134
No FE, controls	0.111	0.014	-0.097	0.004	0.097	0.026	-0.071	0.013
Stock FE	0.121	0.048	-0.073	0.075	0.109	0.061	-0.048	0.137

R^2 of r_{it} on $\Lambda'F$ in the lowest (C1) and highest (C4) cacophony-share quartile inside each quartile of $|\Lambda'F|$. Panel A uses stock fixed effects and controls (H , D , $H \times D$, bid-ask spread) and reports the partial R^2 of $\Lambda'F$; “Mean” is the equal-weighted mean across the four $|\Lambda'F|$ quartiles. Panel B reports that mean under the other specifications; without controls, the entries are the R^2 (no fixed effects) or the within- R^2 (stock fixed effects). Fixed effects are specific to each cell. One-sided p -values ($H_1 : \text{gap} < 0$) from a 999-draw bootstrap over trading days.

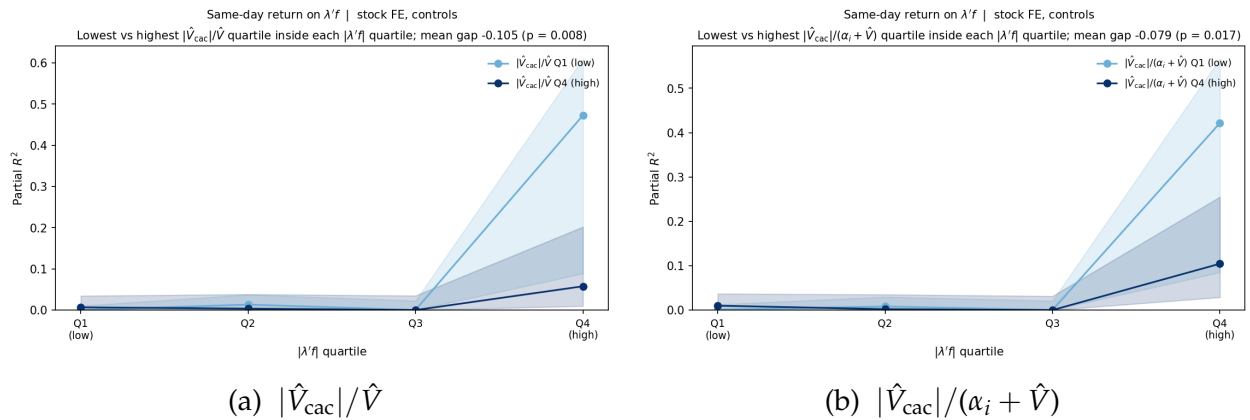


Figure H.3: Partial R^2 in the lowest and highest cacophony-share quartile inside each quartile of $|\Lambda'F|$

Same-day returns on $\Lambda'F$, stock fixed effects and controls. Shaded bands are 90% bootstrap intervals over trading days. The panel titles report the mean gap across quartiles and its one-sided p -value. The horizontal axis runs from the smallest $|\Lambda'F|$ quartile (Q1, left) to the largest (Q4, right).

H.4 Test 2: Can Volume Alone Reproduce the Share Gradient?

Design. When realized volume is considered independently, as expected, the slope of same-day returns on $\Lambda'F$ rises across realized-volume quartiles. (The next-day pattern is non-monotone; see Table H.6.) Because the realized volume and the cacophony share are correlated, each gradient may partly reflect the other. This test takes the volume-only null at face value and asks whether it alone could explain this pattern. I estimate the null model on the full sample,

$$r_{it} = \sum_b c_b \mathbf{1}[V_{it} \in b] + \sum_b g_b \Lambda'F_{it} \mathbf{1}[V_{it} \in b] + \gamma'X_{it} + \mu_i + \delta_t + e_{it}, \quad (9)$$

where b indexes ten bins of realized volume V_{it} , X_{it} are the controls, and μ_i and δ_t are stock and day effects, each included or not as in the main-text grid. I run the same model for the next-day return $r_{i,t+1}$ and then lagged return $r_{i,t}$ is included as a control. The actual and implied quartile slopes below use the same controls and fixed effects as the null model. The slope on $\Lambda'F$ is allowed to vary freely with volume, but with nothing else. I then take the fitted values of this model and compute, inside each cacophony-share quartile, the slope of the fitted values on $\Lambda'F$. This is the slope the null *implies* for each share quartile, given that quartile's mix of high- and low-volume stock-days. If volume is the whole story, the implied Q4 – Q1 gradient equals the actual one. The difference, actual minus implied, is the part of the share gradient that volume cannot account for.

I also run the test in reverse. The null model lets the slope vary only with bins of the cacophony share, and I ask whether it reproduces the realized-volume gradient. Standard errors come from a 499-draw bootstrap over trading days, re-estimating the null model in each draw. As in Test 1, the p -values are one-sided, in the direction the cacophony hypothesis predicts. For cacophony share sorts, the unexplained gradient is negative on the same day and positive on the next day; for realized-volume sorts it is the opposite. (This is as expected. As explained earlier, both explanations rely on the idea that trading is what actively incorporates information into prices.)

Results. Table H.7 reports the headline specification, with stock fixed effects, controls, and ten bins. Table H.8 reports the unexplained gradient under every specification. For same-day returns, volume composition implies a Q4 – Q1 slope gradient of -0.85 across $|\hat{V}_{\text{cac}}|/\hat{V}$ quartiles, against an actual gradient of -1.22 . High-share stock-days are disproportionately low-volume stock-days, and that alone accounts for 70% of the share gradient. The remainder, -0.37 (s.e. 0.20, $p = 0.030$), is the part of the share gradient that volume cannot account for. In the top share quartile, the actual slope is 0.17 while volume composition predicts 0.37. With twenty volume bins the unexplained gradient

is -0.36 (s.e. 0.20).

The reverse test shows the same asymmetry. The share alone reproduces 60% of the realized-volume gradient, leaving $+0.47$ (s.e. 0.27 , $p = 0.043$) unexplained. Each variable therefore carries information about price pass-through that the other does not, but about two-thirds of each single-sort gradient reflects the correlation between them. (For the level share, $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$, volume explains 85% of the gradient, and the residual (-0.17 , s.e. 0.15 , $p = 0.132$) is not significant.)

How much of the overlap is mechanical? Because the share and volume are correlated, each would reproduce part of the other's gradient even if it had no effect of its own on pass-through. A linear benchmark makes this precise. Let the slope on $\Lambda'F$ be $b_V V_{it} + b_S S_{it}$, where S_{it} is the cacophony share, both variables are standardized, and their correlation is ρ . The volume-only null then reproduces a fraction $\rho(b_V + \rho b_S)/(b_S + \rho b_V)$ of the share gradient. This fraction is ρ^2 if only the share matters ($b_V = 0$) and one if only volume matters ($b_S = 0$). The reverse test is symmetric: the share-only null reproduces ρ^2 of the volume gradient if the share has no effect of its own. Table H.9 compares this benchmark with the fractions actually explained, measuring ρ in six ways. The sorts use raw values pooled across stocks, so the pooled correlations are the closest match; the other rows show that the conclusion does not depend on this choice. For $|\hat{V}_{\text{cac}}|/\hat{V}$, the benchmark ranges from 8% to 34%. Volume actually explains 70% of the share gradient, and the share explains 60% of the volume gradient. Each variable therefore reproduces far more of the other's gradient than their correlation alone would generate, and neither reproduces all of it, so both carry their own information about pass-through. For the level share, the benchmark ranges from 7% to 38%, against 85% and 62% actually explained; here volume comes closer to accounting for the whole gradient.

The share of the gradient that volume explains is stable across specifications, at about 70%; only the precision of the remainder changes. With stock and day fixed effects and controls, all gradients are smaller and the unexplained part, -0.20 (s.e. 0.26 , $p = 0.219$), is no longer significant.

For next-day returns, volume implies essentially no gradient across share quartiles (-0.01), against an actual gradient of $+0.19$. The unexplained part is $+0.20$ for $|\hat{V}_{\text{cac}}|/\hat{V}$ ($p = 0.298$) and $+0.16$ for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$ ($p = 0.291$). Both have the sign that delayed incorporation predicts but are not significant. With stock and day fixed effects and controls, the next-day unexplained gradient for $|\hat{V}_{\text{cac}}|/\hat{V}$ is $+0.40$ ($p = 0.062$).

Table H.6: Counterfactual slope gradients, as explained by realized volume

	Q1	Q2	Q3	Q4	Q4–Q1 <i>p</i> -value
<i>No fixed effects</i>					
Same day, r_{it}	0.24***	0.44***	0.82***	1.43***	0.0000***
Same day, r_{it} (controls)	0.26***	0.46***	0.82***	1.42***	0.0000***
Next day, $r_{i,t+1}$	0.25	0.39	0.39	0.15	0.387
Next day, $r_{i,t+1}$ (controls)	0.35	0.51**	0.56**	0.45	0.661
<i>Stock fixed effects</i>					
Same day, r_{it}	0.26***	0.45***	0.83***	1.46***	0.0000***
Same day, r_{it} (controls)	0.27***	0.47***	0.83***	1.45***	0.0000***
Next day, $r_{i,t+1}$	0.27	0.41	0.41	0.15	0.369
Next day, $r_{i,t+1}$ (controls)	0.38*	0.54**	0.59**	0.49	0.685
<i>Day fixed effects</i>					
Same day, r_{it}	0.23***	0.47***	0.64***	1.23***	0.0000***
Same day, r_{it} (controls)	0.23***	0.47***	0.66***	1.23***	0.0000***
Next day, $r_{i,t+1}$	0.22**	0.20**	0.25**	0.01	0.188
Next day, $r_{i,t+1}$ (controls)	0.23*	0.19**	0.24**	0.05	0.198
<i>Stock and day fixed effects</i>					
Same day, r_{it}	0.36***	0.60***	0.78***	1.48***	0.0000***
Same day, r_{it} (controls)	0.35***	0.60***	0.78***	1.49***	0.0000***
Next day, $r_{i,t+1}$	0.34**	0.26**	0.31***	0.02	0.165
Next day, $r_{i,t+1}$ (controls)	0.33**	0.25**	0.32***	0.11	0.217

Table H.7: Counterfactual slope gradients under single-variable null models, stock FE, controls

Horizon	Sorted by	Null: slope depends only on	Actual	Implied	Unexplained	Explained
Same day	$ \hat{V}_{cac} /\hat{V}$	Realized volume	−1.22	−0.85	−0.37** (0.20)	70%
	$ \hat{V}_{cac} /(\alpha_i + \hat{V})$	Realized volume	−1.10	−0.94	−0.17 (0.15)	85%
	Realized volume	$ \hat{V}_{cac} /\hat{V}$	+1.17	+0.70	+0.47** (0.27)	60%
	Realized volume	$ \hat{V}_{cac} /(\alpha_i + \hat{V})$	+1.17	+0.72	+0.45* (0.29)	62%
Next day	$ \hat{V}_{cac} /\hat{V}$	Realized volume	+0.19	−0.01	+0.20 (0.38)	−
	$ \hat{V}_{cac} /(\alpha_i + \hat{V})$	Realized volume	+0.15	−0.00	+0.16 (0.28)	−
	Realized volume	$ \hat{V}_{cac} /\hat{V}$	+0.11	−0.07	+0.18 (0.20)	−
	Realized volume	$ \hat{V}_{cac} /(\alpha_i + \hat{V})$	+0.11	−0.09	+0.20 (0.20)	−

“Actual” is the Q4 – Q1 difference in the slope of returns on ΔF across quartiles of the sort variable, with controls and stock fixed effects. “Implied” is the same difference computed on fitted values from a null model in which the slope on ΔF varies only across ten bins of the other variable. “Unexplained” is actual minus implied. Standard errors in parentheses from a 499-draw bootstrap over trading days in which the null model is re-estimated. “Explained” is implied over actual; it is not reported when it falls outside $[0, 1]$, which happens when the actual gradient is close to zero. Implied slopes by quartile for the first row: 1.22, 0.80, 0.62, 0.37, against actual slopes of 1.39, 0.58, 0.34, 0.17. One-sided tests on the unexplained gradient (see text): *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table H.8: Unexplained slope gradient under single-variable null models, all specifications

Horizon	Sorted by / null depends on Controls	No FE		Stock FE		Day FE		Stock + day FE	
		No	Yes	No	Yes	No	Yes	No	Yes
Same day	$ \hat{V}_{\text{cac}} /\hat{V}$ by Realized volume	-0.32** (0.19)	-0.30* (0.19)	-0.39** (0.19)	-0.37** (0.20)	-0.12 (0.17)	-0.09 (0.18)	-0.21 (0.24)	-0.20 (0.26)
	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$ by Realized volume	-0.11 (0.15)	-0.11 (0.15)	-0.16 (0.15)	-0.17 (0.15)	-0.10 (0.18)	-0.08 (0.19)	-0.18 (0.26)	-0.19 (0.27)
	Realized volume by $ \hat{V}_{\text{cac}} /\hat{V}$	+0.56** (0.24)	+0.52** (0.26)	+0.53** (0.25)	+0.47** (0.27)	+0.40*** (0.14)	+0.39*** (0.15)	+0.47*** (0.20)	+0.46** (0.21)
	Realized volume by $ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	+0.54** (0.26)	+0.51** (0.28)	+0.51** (0.27)	+0.45* (0.29)	+0.41*** (0.14)	+0.41*** (0.15)	+0.48*** (0.20)	+0.48** (0.21)
Next day	$ \hat{V}_{\text{cac}} /\hat{V}$ by Realized volume	+0.38 (0.34)	+0.29 (0.37)	+0.35 (0.35)	+0.20 (0.38)	+0.30* (0.19)	+0.36** (0.20)	+0.37* (0.25)	+0.40* (0.26)
	$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$ by Realized volume	+0.29 (0.24)	+0.22 (0.28)	+0.26 (0.24)	+0.16 (0.28)	+0.21* (0.16)	+0.25* (0.18)	+0.21 (0.21)	+0.24 (0.22)
	Realized volume by $ \hat{V}_{\text{cac}} /\hat{V}$	+0.08 (0.25)	+0.20 (0.20)	+0.05 (0.25)	+0.18 (0.20)	-0.01 (0.14)	-0.03 (0.14)	-0.12 (0.22)	-0.10 (0.21)
	Realized volume by $ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	+0.10 (0.26)	+0.22 (0.20)	+0.06 (0.26)	+0.20 (0.20)	-0.02 (0.15)	-0.02 (0.15)	-0.12 (0.23)	-0.09 (0.22)

Entries are the unexplained Q4 – Q1 gradient (actual minus implied) from Table H.7, with ten bins of the null variable, under each fixed-effect and control specification. Standard errors in parentheses from a 499-draw bootstrap over trading days. One-sided tests (see text): *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

H.5 Test 3: Pooled Regressions with Both Interactions

Finally, I pool all stock-days and estimate

$$r_{it} = b_1 \Lambda' \mathbf{F} + b_2 \Lambda' \mathbf{F} \times s_{it} + b_3 \Lambda' \mathbf{F} \times v_{it} + s_{it} + v_{it} + H + D + H \times D + \text{bid-ask} + \mu_i + \delta_t + e_{it}, \quad (10)$$

where s_{it} is the standardized cacophony share and v_{it} is standardized volume, and μ_i and δ_t are stock and day fixed effects, each included or not as in the main-text grid. The controls are always included. The next-day version (with $r_{i,t+1}$ as the dependent variable) adds r_{it} as a control. Standard errors are two-way clustered by stock and by day. The volume-only null implies $b_2 = 0$.

Linear volume control. Table H.10 (upper panel) shows that, controlling for realized volume, the interaction with $|\hat{V}_{\text{cac}}|/\hat{V}$ is -0.463^{***} (s.e. 0.179) with stock and day fixed effects, and between -0.355^* and -0.444^{**} in the other three specifications. At the same time the interaction with realized volume is 0.155^{***} . The two variables carry separate information with opposite signs, which is the prediction of the cacophony hypothesis.²¹

²¹For $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$ the interaction is -0.268^{**} (s.e. 0.134) with stock and day fixed effects, but it is not significant without day fixed effects (-0.173 , s.e. 0.168, with stock fixed effects only).

Table H.9: Expected and actual overlap between the share and volume gradients

		Volume explains share gradient		Share explains volume gradient	
Correlation of share with log turnover	ρ	Expected	Actual	Expected	Actual
<i>Panel A: Share $\hat{V}_{\text{cac}} /\hat{V}$</i>					
Spearman, pooled	−0.50	25%		25%	
Pearson, pooled	−0.50	25%		25%	
Pearson, within stock	−0.29	8%	70%	8%	60%
Pearson, within stock, net of controls	−0.59	34%		34%	
Pearson, within stock and day	−0.31	10%		10%	
Pearson, within stock and day, net of controls	−0.53	29%		29%	
<i>Panel B: Share $\hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$</i>					
Spearman, pooled	−0.62	38%		38%	
Pearson, pooled	−0.60	36%		36%	
Pearson, within stock	−0.26	7%	85%	7%	62%
Pearson, within stock, net of controls	−0.50	25%		25%	
Pearson, within stock and day	−0.27	7%		7%	
Pearson, within stock and day, net of controls	−0.42	17%		17%	

ρ is the correlation between the cacophony share and log turnover, on stock-days with all controls observed. “Within stock” removes stock means from both variables; “within stock and day” removes stock and day effects; “net of controls” also partials out the controls of the null model. “Expected” is ρ^2 : the fraction of the other variable’s Q4 – Q1 slope gradient that the explaining variable would reproduce if it had no effect of its own on the slope (see text). “Actual” is the explained fraction from Table H.7 (same-day returns, stock fixed effects, controls, ten bins). Across the eight fixed-effect and control specifications, volume explains 67% – 80% of the $|\hat{V}_{\text{cac}}|/\hat{V}$ gradient and that share explains 53% – 61% of the volume gradient; for $|\hat{V}_{\text{cac}}|/(\alpha_i + \hat{V})$, the ranges are 71% – 89% and 54% – 62%.

Flexible volume control. To rule out that the share proxies for nonlinear effects of volume, I replace $\Lambda'F \times v_{it}$ with $\Lambda'F$ interacted with a full set of ten realized-volume decile dummies, along with the decile main effects. The slope on $\Lambda'F$ can then vary arbitrarily with volume. The interaction with $|\hat{V}_{cac}|/\hat{V}$ strengthens: -0.551^{***} (s.e. 0.199) with stock and day fixed effects and -0.455^{**} (s.e. 0.195) with stock fixed effects only. With stock fixed effects, the decile-specific loadings on $\Lambda'F$ increase from 0.24 in the lowest decile to 1.17 in the highest. With day fixed effects, the loadings are, as expected, flatter (0.54 to 0.63). For $|\hat{V}_{cac}|/(\alpha_i + \hat{V})$ the interaction is -0.427^{**} (s.e. 0.179) with stock and day fixed effects.

CAPM benchmark. As in Test 1, I repeat both regressions for same-day returns with the CAPM fitted return $\hat{\beta}_i r_{m,t}$ in place of $\Lambda'F$, with the same controls and fixed effects (Table H.12). The share interaction is negative here too, and of similar size. Controlling for realized volume, the interaction of $\hat{\beta}_i r_{m,t}$ with $|\hat{V}_{cac}|/\hat{V}$ is -0.411^{***} (s.e. 0.109) with stock and day fixed effects, against -0.463^{***} for $\Lambda'F$. With decile-specific loadings it is -0.404^{***} (s.e. 0.099), and for $|\hat{V}_{cac}|/(\alpha_i + \hat{V})$ it is -0.329^{***} (s.e. 0.098). Holding volume fixed, high-share stock-days pass less of the market return into prices as well as less of the narrative-implied return, so the pooled share effect, like the R^2 gap of Test 1, is not specific to the narrative factors. Volume, by contrast, works in opposite directions for the two regressors. The interaction with realized volume is -0.102^* for the market return, against 0.155^{***} for $\Lambda'F$, and with stock and day fixed effects the market loading falls from 0.90 in the lowest volume decile to 0.42 in the highest. As with $\Lambda'F$, the unscaled numerator $|\hat{V}_{cac}|$ does not interact significantly with the market return in any specification.

Next-day returns. Table H.11 reports the same regressions for next-day returns. None of the share interactions is significant in any specification. The point estimates for the two shares range from +0.05 to +0.19, the sign predicted by delayed incorporation.

H.6 Cacophony Alone

The numerator $|\hat{V}_{cac}|$, unscaled by fitted volume, provides a useful comparison. Within volume deciles, a high $|\hat{V}_{cac}|$ is associated with a modest loss of R^2 (-0.097 , $p = 0.017$, with stock fixed effects and controls; Table H.2) but no change in the same-day slope on $\Lambda'F$, in any specification of Test 3 (Table H.10). Loud cacophony on its own adds noise to same-day returns without reducing how much of the narrative-implied return reaches prices. The same-day pass-through effect appears only once the suppressed volume is

Table H.10: Pooled regressions: $\Lambda'F$ interacted with cacophony share and with volume, same-day returns

Share	Volume control	$\lambda'f \times \text{share}$				$\lambda'f \times \text{volume}$			
		No FE	Stock FE	Day FE	Stock + day FE	No FE	Stock FE	Day FE	Stock + day FE
<i>Linear volume interaction</i>									
$ \hat{V}_{\text{cac}} /\hat{V}$	Realized volume	−0.355* (0.186)	−0.403** (0.186)	−0.444** (0.179)	−0.463*** (0.179)	0.381*** (0.113)	0.360*** (0.113)	0.164*** (0.051)	0.155*** (0.052)
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	Realized volume	−0.118 (0.168)	−0.173 (0.168)	−0.237* (0.134)	−0.268** (0.134)	0.460*** (0.129)	0.436*** (0.132)	0.224*** (0.054)	0.210*** (0.055)
$ \hat{V}_{\text{cac}} $	Realized volume	0.113 (0.161)	0.076 (0.163)	0.007 (0.041)	−0.020 (0.041)	0.494*** (0.109)	0.497*** (0.109)	0.325*** (0.085)	0.325*** (0.084)
$ \hat{V}_{\text{cac}} /\hat{V}$	$\hat{V}$	0.074 (0.157)	0.036 (0.161)	0.113** (0.049)	0.085* (0.050)	0.597*** (0.100)	0.585*** (0.100)	0.496*** (0.061)	0.486*** (0.062)
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	$\hat{V}$	0.273* (0.163)	0.238 (0.166)	0.310*** (0.058)	0.282*** (0.059)	0.656*** (0.102)	0.646*** (0.103)	0.564*** (0.068)	0.554*** (0.069)
<i>$\lambda'f \times \text{realized-volume decile dummies}$</i>									
$ \hat{V}_{\text{cac}} /\hat{V}$	Deciles	−0.406** (0.196)	−0.455** (0.195)	−0.534*** (0.202)	−0.551*** (0.199)	1.22/0.20	1.17/0.24	0.47/0.34	0.63/0.54
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	Deciles	−0.201 (0.182)	−0.258 (0.180)	−0.400** (0.181)	−0.427** (0.179)	1.51/0.28	1.46/0.34	0.74/0.59	0.88/0.80
$ \hat{V}_{\text{cac}} $	Deciles	0.122 (0.161)	0.085 (0.164)	0.013 (0.041)	−0.015 (0.041)	1.79/0.27	1.79/0.26	1.35/0.46	1.50/0.62

The dependent variable is r_{it} ; $N = 40,572$. Share and volume are standardized. All regressions include $\Lambda'F$, the share and volume main effects, H , D , $H \times D$, and the relative bid-ask spread. In the $|\hat{V}_{\text{cac}}|$ rows the share is a rescaled $H \times D$, so $H \times D$ is not entered separately. In the lower panel, the volume columns report the loading on $\Lambda'F$ in the highest and the lowest realized-volume decile (D10/D1) under each fixed-effect specification. Standard errors in parentheses are clustered by stock and by day. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table H.11: Pooled regressions: $\Lambda'F$ interacted with cacophony share and with volume, next-day returns

Share	Volume control	$\lambda'f \times \text{share}$				$\lambda'f \times \text{volume}$			
		No FE	Stock FE	Day FE	Stock + day FE	No FE	Stock FE	Day FE	Stock + day FE
<i>Linear volume interaction</i>									
$ \hat{V}_{\text{cac}} /\hat{V}$	Realized volume	0.164 (0.167)	0.134 (0.174)	0.087 (0.070)	0.070 (0.080)	0.009 (0.112)	−0.000 (0.112)	−0.055 (0.055)	−0.058 (0.054)
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	Realized volume	0.159 (0.155)	0.128 (0.157)	0.062 (0.043)	0.046 (0.049)	0.014 (0.134)	0.005 (0.133)	−0.062 (0.067)	−0.063 (0.066)
$ \hat{V}_{\text{cac}} $	Realized volume	0.106 (0.136)	0.080 (0.140)	0.023 (0.048)	0.009 (0.046)	−0.060 (0.114)	−0.056 (0.117)	−0.087 (0.069)	−0.084 (0.072)
$ \hat{V}_{\text{cac}} /\hat{V}$	$\hat{V}$	0.105 (0.169)	0.064 (0.173)	−0.007 (0.077)	−0.026 (0.075)	−0.022 (0.130)	−0.027 (0.122)	−0.106 (0.106)	−0.107 (0.104)
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	$\hat{V}$	0.080 (0.163)	0.040 (0.167)	−0.027 (0.095)	−0.044 (0.095)	−0.042 (0.152)	−0.047 (0.145)	−0.115 (0.119)	−0.115 (0.119)
<i>$\lambda'f \times \text{realized-volume decile dummies}$</i>									
$ \hat{V}_{\text{cac}} /\hat{V}$	Deciles	0.172 (0.169)	0.142 (0.177)	0.112 (0.088)	0.094 (0.099)	0.57/0.32	0.57/0.35	0.20/0.30	0.25/0.37
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	Deciles	0.185 (0.158)	0.154 (0.160)	0.103 (0.067)	0.086 (0.075)	0.57/0.24	0.57/0.28	0.17/0.25	0.23/0.32
$ \hat{V}_{\text{cac}} $	Deciles	0.101 (0.137)	0.076 (0.140)	0.023 (0.048)	0.009 (0.046)	0.39/0.41	0.41/0.42	0.04/0.31	0.11/0.37

The dependent variable is $r_{i,t+1}$. Same specification as Table H.10, with the same-day return r_{it} added as a control. Standard errors in parentheses are clustered by stock and by day. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table H.12: Pooled regressions: CAPM fitted return interacted with cacophony share and with volume, same-day returns

Share	Volume control	$\hat{\beta}_i r_{m,t} \times \text{share}$				$\hat{\beta}_i r_{m,t} \times \text{volume}$			
		No FE	Stock FE	Day FE	Stock + day FE	No FE	Stock FE	Day FE	Stock + day FE
<i>Linear volume interaction</i>									
$ \hat{V}_{\text{cac}} /\hat{V}$	Realized volume	−0.193*** (0.074)	−0.198*** (0.075)	−0.413*** (0.107)	−0.411*** (0.109)	−0.066 (0.053)	−0.068 (0.052)	−0.104* (0.055)	−0.102* (0.054)
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	Realized volume	−0.186*** (0.072)	−0.193** (0.076)	−0.332*** (0.098)	−0.329*** (0.098)	−0.061 (0.054)	−0.065 (0.054)	−0.090 (0.059)	−0.087 (0.057)
$ \hat{V}_{\text{cac}} $	Realized volume	−0.055 (0.047)	−0.059 (0.048)	−0.129 (0.084)	−0.127 (0.085)	0.024 (0.034)	0.024 (0.034)	0.043* (0.024)	0.043* (0.022)
$ \hat{V}_{\text{cac}} /\hat{V}$	$\hat{V}$	−0.081 (0.063)	−0.088 (0.064)	−0.225*** (0.082)	−0.223*** (0.084)	0.029 (0.020)	0.028 (0.020)	0.036 (0.029)	0.039 (0.029)
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	$\hat{V}$	−0.013 (0.057)	−0.016 (0.057)	−0.045 (0.062)	−0.041 (0.063)	0.052*** (0.020)	0.052*** (0.020)	0.089** (0.038)	0.092** (0.038)
$\hat{\beta}_i r_{m,t} \times \text{realized-volume decile dummies}$									
$ \hat{V}_{\text{cac}} /\hat{V}$	Deciles	−0.208*** (0.061)	−0.213*** (0.064)	−0.407*** (0.096)	−0.404*** (0.099)	0.74/1.09	0.73/1.11	0.42/0.90	0.42/0.90
$ \hat{V}_{\text{cac}} /(\alpha_i + \hat{V})$	Deciles	−0.217*** (0.055)	−0.226*** (0.062)	−0.370*** (0.082)	−0.367*** (0.085)	0.76/1.19	0.75/1.22	0.53/1.18	0.53/1.18
$ \hat{V}_{\text{cac}} $	Deciles	−0.057 (0.045)	−0.060 (0.047)	−0.131 (0.082)	−0.129 (0.082)	1.02/0.92	1.02/0.92	1.01/0.83	1.00/0.83

The dependent variable is r_{it} . Same specification as Table H.10, with the CAPM fitted return $\hat{\beta}_i r_{m,t}$ in place of $\Delta'F$, where $r_{m,t}$ is the CRSP market return and $\hat{\beta}_i$ is each stock's full-sample market beta. In the lower panel, the volume columns report the loading on $\hat{\beta}_i r_{m,t}$ in the highest and the lowest realized-volume decile (D10/D1). Standard errors in parentheses are clustered by stock and by day. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

scaled by fitted volume. What matters is the *share* of potential trade that cacophony stifles, not how “loud” the cacophony is in absolute terms.

I Alternative Text Approaches: Topic Modeling

In this appendix, I ask whether the cacophony volume-dampening result depends on representing the news as narratives, or whether a standard text-as-data representation of the same news would suffice. To this end, I replace narratives with topics from Latent Dirichlet Allocation (LDA; Blei et al., 2003), one of the workhorse models of the text-in-finance literature (e.g., Bybee et al., 2024), and – through a variety of configurations which run the gamut between direct topic modeling and hybrid approaches between topic modeling and my methodology – I build topic-based analogues of narrative price pressure $\tau_{i,t}$, dispersion $H_{i,t}$, directional disagreement $D_{i,t}$ and cacophony $H_{i,t} \times D_{i,t}$ with the same formulas as for narratives. I then re-do the volume analysis of the main text in two ways:

1. *Horse-race*. The topic-modeling analogues of H , D , $H \times D$ and τ replace the narrative ones. If topics carry the same information as narratives, the topic-based interaction should also have a negative coefficient.
2. *Control*. The topic-based H , D and τ , or the topic factors themselves, are added next to the narrative measures. If the narrative result only reflects what topics already capture, the narrative interaction should shrink towards zero.

Intuitively, these two approaches answer slightly different questions: the first asks whether topics and narratives are equally well-suited to discover evidence of the cacophony conjecture. The second asks whether narratives contain something which is not contained in topics. I find, first, that in a horse-race, topic models struggle to reproduce a cacophony volume-dampening effect and, second, that even when included as controls for narratives, they do not negate the effect of narrative cacophony.

To the degree that topic models can be thought of as measuring the substance of discourse and narratives its structure, this suggests that the cacophony volume-dampening effect resides primarily in the structure. That is, agents' reluctance to trade is attributable to *how* new developments are discussed, and not *what* precisely is being discussed.

Because no single way of turning topics into stock-level measures is standard, I build 18 variants: for each text starting-point (raw articles, structured summaries as “stories”), three exposure models (market-wide, industry, and industry with time-varying topic regimes) crossed with three choices of topic factors (two aggregation conventions and two selection rules, Section I.2). These hybrid approaches increasingly add elements of my narrative methodology to topics, so that the “final” model considered is identical to my pipeline (with fused LASSO-extracted regimes, etc.) except that the cluster-extraction uses narrative scoring and not topic modeling. The sample is the one of the main text

throughout: 483 S&P 500 stocks in 19 two-digit NAICS sectors over the 84 trading days from 1 April to 31 July 2025, for 40,572 stock-days.

I.1 Topic Models

Corpora. The article corpus contains 21,973 Factiva articles after removing duplicates, identified by the first ten lines of the Factiva header. I keep the body text that follows the copyright line. The story corpus contains 21,771 articles; each story’s bullet points are concatenated into one document. Every document is dated by the publication date of its article.

Preprocessing. I lemmatize each document with spaCy and keep only nouns, verbs, adjectives and adverbs. I remove English stopwords (NLTK list), a few formatting artifacts of the Factiva files, and tokens of two characters or fewer. Frequent two- and three-word expressions (e.g., “trade deal”, “trade war”) are merged into single tokens with gensim’s phrase detection (minimum counts of 20 and 10, threshold 10). The dictionary keeps every token that appears in at least five documents. I do not drop very frequent tokens: the corpus is about a single policy theme, so words such as “tariff” appear in most documents but their weight still differs across topics.

Estimation and number of topics. I estimate LDA by online variational Bayes (Hoffman et al., 2010) with gensim (chunks of 2,000 documents, 10 passes, 400 inference iterations, an asymmetric document–topic prior, a learned topic–word prior, fixed seed). I estimate the model for $K \in \{10, 15, 20, 25, 30, 40, 50\}$ topics and keep the K with the highest C_V topic coherence Röder et al. (2015): in other words, the number and size of topics is endogenous and is optimized by the algorithm. Table I.1 reports the scores. Coherence selects $K = 25$ for the articles and $K = 15$ for the stories.

Each model yields, for every document d , a vector of topic weights $\theta_{d,1}, \dots, \theta_{d,K}$ that sums to one. Philosophically, this constitutes a major difference between topics and narratives: narratives assign an article to exactly one narrative (possibly a singleton), whereas an article can contain multiple topics. This supports the interpretation that narratives bear on the structure of discourse and topics are more about its substance.

Table I.1: Topic coherence by number of topics

Number of topics K	Raw articles	Condensed stories
10	0.378	0.406
15	0.387	0.437
20	0.419	0.418
25	0.426	0.407
30	0.426	0.418
40	0.415	0.385
50	0.426	0.411

C_V coherence of the LDA model estimated with K topics on each corpus.
 Bold: selected model.

I.2 Daily Topic Factors

Aggregation. Let $\mathcal{D}_t$ be the set of documents dated t and N_t its size. I aggregate document weights into daily topic factors in two ways:

$$f_{k,t}^{\text{shares}} = \frac{1}{N_t} \sum_{d \in \mathcal{D}_t} \theta_{d,k}, \quad f_{k,t}^{\text{counts}} = \sum_{d \in \mathcal{D}_t} \theta_{d,k}. \quad (11)$$

Shares are the daily average topic weights used by [Bybee et al. \(2024\)](#); they sum to one across topics each day and measure the composition of the news. *Counts* measure the effective number of documents on each topic and therefore also scale with the amount of news.

Topic selection. The narrative measures of the main text aggregate over a small number of narratives, so I reduce the topic set before building the dispersion measures. I consider two selection rules.

- *LASSO 5.* I regress daily stock returns $r_{i,t}$, pooled across stocks, on all K standardized topic factors with a LASSO penalty chosen by five-fold cross-validation, and keep the five topics with the largest absolute coefficients. This follows the logic of selecting the topics that matter for returns, as in [Bybee et al. \(2024\)](#). (However, it adds a bit of circularity because it selects the important narratives for their ability to explain returns, and then uses them to explain returns.)
- *Top 15.* I rank topics by their total prominence over the sample, $\sum_t f_{k,t}^{\text{counts}}$, keep the 14 most prominent ones, and pool the remaining topics into a 15th factor. I choose 15 because that is the number of narratives in the main text. I build this variant only with counts: with shares, the 15 factors would sum to one every day and be

collinear with the intercept. For the stories ($K = 15$), this rule keeps every topic, the 15th factor being the least prominent topic.

Table I.2 lists the LASSO-selected topics. For the articles, they are topics that comove with returns rather than the core tariff topics: shipping and ports, war and sanctions involving Russia, trade balances, consumer products, and banking and credit (with shares) or agricultural exports (with counts). All of them lie outside the 14 most prominent article topics, which are generic tariff, trade-negotiation and macroeconomic topics (the most prominent one is “tariff, say, country, trade, good, cent, impose, administration”). For the stories, the topic selected first under both conventions (topic 7, “lumber, committee, user, uphold, ...”) is the least prominent of the 15. The top-15 rule is meant to address this: it builds the measures from the topics that dominate the coverage rather than from those that ex-post best fit returns.

I.3 Stock Exposures and Topic Regimes

The narrative measures weight each narrative by its implied price pressure on the stock. The topic analogue needs an exposure $\lambda_{i,k}$ of stock i to topic k , and a signed daily topic factor. I use three exposure models.

Market exposure. The pooled OLS coefficients $\hat{\beta}_k$ of Table I.2 (or of the top-15 factors) are used for every stock: $\lambda_{i,k} = \hat{\beta}_k$. The resulting measures vary only across days.

Industry exposure. In an intermediate variant, I allow for industry-heterogeneity in exposure, but no time-variation in what a topic means (i.e., no “regimes”). That is, I estimate, separately for each two-digit NAICS sector g , the linear mixed model

$$r_{i,t} = \alpha_g + \sum_k \gamma_{k,g} f_{k,t} + \sum_k u_{i,k} f_{k,t} + \varepsilon_{i,t}, \quad u_{i,k} \sim \mathcal{N}(0, \sigma_{k,g}^2), \quad (12)$$

by restricted maximum likelihood, with independent random slopes across topics (Gelman and Hill, 2006). The exposure of stock i is the fixed effect of its sector, $\lambda_{i,k} = \hat{\gamma}_{k,g(i)}$. I do not add the stock-level deviations $\hat{u}_{i,k}$: a likelihood-ratio test of model (12) against a sector-level OLS regression (estimated by maximum likelihood) rarely rejects the restriction that all random-slope variances are zero: at the 5% level it rejects in 8 of the 228 sector-by-variant tests, 6 of them in a single variant. Table I.3 reports the rejections and the marginal R^2 of the sector models.

Industry exposure with topic regimes. This is the exact analogue of what I do with narratives: time-varying regimes and constant industry-level exposure.

Table I.2: Topics selected by the LASSO

Topic	Eight most probable words	<i>t</i> -stat.
<i>A. Raw articles, shares</i>		
21	port, ship, home, shipment, housing, buyer, good, shipping	1.23
20	report, say, war, russian, military, sanction, attack, also	−0.70
19	balance, luxury, deficit, net, surplus, calculate, trade deficit, startup	0.10
6	bank, loan, financial, debt, credit, capital, payment, cash	1.24
4	product, say, cent, australian, good, brand, make, buy	−1.66
<i>B. Raw articles, counts</i>		
19	balance, luxury, deficit, net, surplus, calculate, trade deficit, startup	0.19
21	port, ship, home, shipment, housing, buyer, good, shipping	2.04
20	report, say, war, russian, military, sanction, attack, also	−0.66
13	soybean, export, duty, price, cotton, seafood, grain, shrimp	1.10
4	product, say, cent, australian, good, brand, make, buy	−1.15
<i>C. Condensed stories, shares</i>		
7	lumber, committee, user, uphold, aircraft, advertising, presidential election, escalating trade war	1.95
3	dollar, investor, bank, fund, currency, loan, debt, sell	1.69
12	company, indian, product, manufacturing, pharmaceutical, export, manufacturer, production	0.99
2	trade, tariff, negotiation, deal, talk, trade deal, agreement, agree	1.55
9	canadian, worker, government, election, win, make, call, campaign	−0.27
<i>D. Condensed stories, counts</i>		
7	lumber, committee, user, uphold, aircraft, advertising, presidential election, escalating trade war	0.91
3	dollar, investor, bank, fund, currency, loan, debt, sell	1.64
6	sanction, oil, russian, barrel, energy, oil price, war, supply	−2.33
1	chinese, global, trade, economic, economy, country, trade war, investment	−0.51
14	global, year, growth, fall, cent, rise, inflation, market	−2.26

The five topics with the largest absolute coefficients in a pooled, cross-validated LASSO regression of daily stock returns on all standardized daily topic factors, for each corpus and aggregation convention (shares or counts, equation (11)). Topic numbers refer to the model of each corpus ($K = 25$ for articles, $K = 15$ for stories). Multi-word tokens are shown with spaces. *t*-stat.: *t*-statistic of the topic factor in the pooled OLS regression of returns on the five selected factors (standard errors two-way clustered by stock and by day); its coefficient is the market-wide exposure $\hat{\beta}_k$ of Section I.3.

Topic factors are non-negative; with time-invariant exposures, the sign of the contribution $\lambda_{i,k}f_{k,t}$ is therefore fixed, and directional disagreement can only vary through the mix of topics. To give topics a time-varying direction, I estimate topic-specific, piecewise-constant pricing coefficients on the daily return of the tariff long-short commodity portfolio, R_t^{LS} (the same series that enters the regressions below as a control). With x_t a constant and the standardized topic factors, I solve the fused LASSO (Tibshirani et al., 2005)

$$\min_{\beta_1, \dots, \beta_T} \sum_{t=1}^T (R_t^{LS} - x_t' \beta_t)^2 + \lambda_{tv} \sum_{t=2}^T \sum_k |\beta_{k,t} - \beta_{k,t-1}|, \quad (13)$$

which yields piecewise-constant coefficient paths. I choose λ_{tv} following the same rule as in the main text, to maximize the average size of a regime change. I then re-estimate model (12) with $\tilde{F}_{k,t}$ in place of $F_{k,t}$ and set $\lambda_{i,k} = \hat{\gamma}_{g(i),k}$ as before.

Table I.3 shows that the selected regime paths are flexible: between 37 and 63 coefficient changes in total, summed over all coefficient paths, across the 84 days, and an in-sample R^2 of at least 0.99. The paths should be read as a decomposition of the tariff factor into topic contributions, not as a forecasting model.

Table I.3: Industry exposure models and topic regimes

Corpus	Factor	Topics	Regimes	Regime fit			Sector models		
				λ_{tv}	J	R^2	Median R^2	Min-max R^2	LR rej.
Articles	Shares	LASSO 5	No	—	—	—	0.017	0.005–0.033	0
Articles	Counts	LASSO 5	No	—	—	—	0.076	0.012–0.153	6
Articles	Counts	Top 15	No	—	—	—	0.115	0.057–0.177	0
Articles	Shares	LASSO 5	Yes	1.50×10^{-8}	62	1.000	0.025	0.003–0.061	0
Articles	Counts	LASSO 5	Yes	1.88×10^{-4}	55	0.999	0.066	0.015–0.126	0
Articles	Counts	Top 15	Yes	1.33×10^{-4}	58	1.000	0.117	0.063–0.215	1
Stories	Shares	LASSO 5	No	—	—	—	0.045	0.025–0.090	0
Stories	Counts	LASSO 5	No	—	—	—	0.105	0.054–0.208	1
Stories	Counts	All 15	No	—	—	—	0.165	0.077–0.266	0
Stories	Shares	LASSO 5	Yes	1.62×10^{-4}	63	1.000	0.037	0.016–0.068	0
Stories	Counts	LASSO 5	Yes	2.58×10^{-4}	37	0.999	0.085	0.029–0.154	0
Stories	Counts	All 15	Yes	1.01×10^{-3}	51	0.991	0.145	0.051–0.232	0

One row per industry-exposure variant. Factor: shares or counts (equation (11)). Topics: the five LASSO-selected topics, or the 14 most prominent topics plus the pooled rest (for stories, all 15 topics). Regime fit: penalty λ_{tv} selected in equation (13), number J of non-zero coefficient changes summed over all coefficient paths, and in-sample R^2 of the fused-LASSO fit of R_t^{LS} ($T = 84$). Sector models: marginal R^2 (share of return variance explained by the sector fixed effects) of model (12) across the 19 NAICS sectors, and number of sectors (out of 19) in which a likelihood-ratio test rejects zero random-slope variances at the 5% level. All 483 stocks are covered.

I.4 Topic-Based Dispersion, Disagreement and Price Pressure

For each variant, let $z_{k,t}$ be the topic factor ($F_{k,t}$ without regimes, $\tilde{F}_{k,t}$ with regimes) and $c_{i,k,t} = \lambda_{i,k} z_{k,t}$ the contribution of topic k to stock i on day t . Exactly as for narratives,

$$\tau_{i,t}^{\text{topic}} = \sum_k |c_{i,k,t}|, \quad (14)$$

$$H_{i,t}^{\text{topic}} = - \sum_k p_{i,k,t} \ln p_{i,k,t}, \quad p_{i,k,t} = \frac{|c_{i,k,t}|}{\tau_{i,t}^{\text{topic}}}, \quad (15)$$

$$D_{i,t}^{\text{topic}} = 1 - \frac{|\sum_k c_{i,k,t}|}{\tau_{i,t}^{\text{topic}}}. \quad (16)$$

τ^{topic} is the total topic-implied price pressure, H^{topic} measures how evenly that pressure is spread across topics, and D^{topic} measures how much the topic contributions offset each other. H^{topic} is bounded by $\ln 5 \approx 1.61$ or $\ln 15 \approx 2.71$ depending on the topic set, so coefficients are not comparable in size across variants or with the narrative coefficients; their signs and significance are.

The 18 variants combine: two text corpora (raw articles, condensed stories); three exposure models (market, industry, industry with regimes); and three topic sets (LASSO 5 with shares, LASSO 5 with counts, top 15 with counts). Market-exposure measures vary only across days.

I.5 Regression Design

All regressions take the form of the main-text volume regression,

$$\ln \text{TO}_{i,t} = \alpha_i + b_H H_{i,t} + b_D D_{i,t} + b_{HD} H_{i,t} D_{i,t} + b_\tau \tau_{i,t} + \gamma' X_{i,t} + \varepsilon_{i,t}, \quad (17)$$

where $\ln \text{TO}_{i,t}$ is log volume and α_i is a stock fixed effect. Standard errors are clustered by stock. I use the three control sets of the main text:

- *Base*: $|r_{i,t}|$, $\ln \text{TO}_{i,t-1}$ and $\ln(1 + \text{no. articles}_t)$;
- $+R^{LS}$: Base plus the tariff long–short portfolio return R_t^{LS} ;
- *Full*: $+R^{LS}$ plus VIX_t , the daily trade policy uncertainty index of [Baker et al. \(2016\)](#) (TPU_t), and the relative bid–ask spread $(\text{ask} - \text{bid})/\text{mid}_{i,t}$.

In the substitution regressions, H , D , $H \times D$ and τ in equation (17) are the topic-based measures of equations (14)–(16). In the control regressions, they are the narrative measures, and I add H^{topic} , D^{topic} and τ^{topic} as further regressors. In two additional

control regressions per corpus, I add the five LASSO-selected topic factors themselves (shares or counts) instead of measures built from them, which is the closest analogue to how topic models enter return regressions in Bybee et al. (2024). All regressions use the same 40,572 stock-days.

I.6 Results

Horse-race. Table I.4 reports the horse-race regressions with the full control set. With narratives, dispersion and directional disagreement each raise volume, and cacophony (their interaction) lowers it. Topics do not reproduce this pattern. In 13 of the 18 variants, the topic-based interaction $H^{\text{topic}} \times D^{\text{topic}}$ has a *positive* coefficient, significant at the 5% level. It is insignificant in one variant and negative in four. The positive sign holds for both corpora and for every exposure model: it is the sign the canonical disagreement view predicts, the opposite of the narrative result. Running LDA on the condensed stories instead of the raw articles does not change this. The positive sign appears in six of the nine story-based variants, so feeding the topic model the text units of the narrative pipeline is not enough.

The four exceptions all use industry exposures with topic regimes: the two article-based variants with LASSO-5 topics, and the story-based variants with LASSO-5 shares and with all 15 topics. They match the narrative signs (H and D positive, $H \times D$ negative). Topic measures therefore come closest to the narrative result when their contributions are given a time-varying direction. The pattern is fragile, however. The other two regime-based variants (article-based top 15, story-based LASSO 5 with counts) have a positive interaction. Only the two article-based exceptions are negative and significant under all three control sets (Table I.6).

Within R^2 is similar across specifications (0.454 to 0.471, against 0.460 with narratives). The two highest values come from the article-based count measures with market and industry exposure, whose interaction is positive. Market-exposure measures vary only by date. With stock fixed effects only, any date-level series that tracks market-wide volume raises the within R^2 , so the R^2 comparison says little about which representation of the news is closer to the mechanism.

Control. Table I.5 adds the topic-based measures to the narrative ones. The narrative cacophony coefficient stays negative and significant at the 1% level in all 21 specifications. With one exception, it lies between -0.606 and -0.739 , against -0.647 without topic measures. (The exception adds the five article topic shares directly as regressors – i.e., not underlying the disagreement and cacophony measures, but the actual topics. There,

the coefficient falls to -0.353 but remains significant at the 1% level with a t -statistic close to 10. These five shares are date-level variables, and they absorb part of the day-to-day variation in volume that the narrative measures also capture.) The article topic factors measured as counts, and the story topic factors, leave the coefficient essentially unchanged. Topic information raises the within R^2 by at most 0.014. This holds even for the four regime-based topic measures with a negative interaction in the substitution regressions: with them added, the narrative coefficient is -0.663 , -0.642 , -0.606 and -0.655 . This confirms that topic measures do not capture the primary variation that drives the narrative result.

Control sets. Table I.6 reports the interaction coefficient for every variant under all three control sets. The main conclusions do not depend on the controls.

- In the horse-race regressions, the topic-based interaction is positive and significant at the 5% level in variants number 10, 12 and 13 of the 18 under the Base, $+R^{LS}$ and Full sets, and negative and significant in 2, 3 and 4.
- In the control regressions, the narrative interaction remains significant at the 1% level in every cell. It ranges from -0.223 to -0.679 (Base), from -0.248 to -0.669 ($+R^{LS}$) and from -0.353 to -0.739 (Full). The smallest magnitude is always the article-topic-shares specification.

Interpretation. A topic is a distribution over words. Two topics differ when the coverage uses different vocabulary (ports and shipping, banks and credit, sanctions and war), so topic dispersion therefore signals that the news is spread over many subjects. This is consistent with more information, not with more confusion on how to interpret the information. In fact, the presence of more information to trade on is a plausible explanation for the positive interaction found for most topic measures. Narratives instead offer fundamentally and structurally different story-telling patterns, and so their multiplicity reflects a presence of genuinely different reasoning strategies – and the attendant interpretational complexity.

Table I.4: Substitution: topic-based measures replace narrative measures

Topic-based measure				H	D	$H \times D$	τ	Within R^2
Exposure	Factor	Topics	Regimes					
Narratives (main text)				0.418*** (0.028)	1.127*** (0.068)	-0.647*** (0.036)	-0.153 (0.108)	0.460
<i>A. Topics estimated on raw articles ($K = 25$)</i>								
Market	Shares	LASSO 5	No	-1.737*** (0.170)	-3.324*** (0.281)	2.372*** (0.206)	0.764* (0.426)	0.455
Market	Counts	LASSO 5	No	-4.133*** (0.105)	-6.869*** (0.174)	4.923*** (0.126)	0.827*** (0.175)	0.471
Market	Counts	Top 15	No	-3.264*** (0.747)	-8.755*** (1.777)	3.625*** (0.782)	0.270*** (0.048)	0.456
Industry	Shares	LASSO 5	No	-0.481*** (0.104)	-1.017*** (0.174)	0.714*** (0.126)	-0.400 (0.378)	0.454
Industry	Counts	LASSO 5	No	-2.233*** (0.112)	-3.682*** (0.186)	2.613*** (0.134)	-0.037 (0.123)	0.463
Industry	Counts	Top 15	No	-0.552* (0.319)	-1.992** (0.785)	0.735** (0.339)	0.076* (0.041)	0.455
Industry	Shares	LASSO 5	Yes	0.023 (0.016)	0.259*** (0.031)	-0.207*** (0.028)	-5.298*** (0.483)	0.455
Industry	Counts	LASSO 5	Yes	0.089*** (0.013)	0.361*** (0.038)	-0.291*** (0.030)	4.037*** (0.310)	0.458
Industry	Counts	Top 15	Yes	-0.889*** (0.147)	-1.702*** (0.369)	0.763*** (0.166)	0.004 (0.044)	0.456
<i>B. Topics estimated on condensed stories ($K = 15$)</i>								
Market	Shares	LASSO 5	No	-0.219*** (0.082)	-15.520*** (1.830)	11.244*** (1.348)	1.095*** (0.320)	0.458
Market	Counts	LASSO 5	No	-1.669*** (0.137)	-3.389*** (0.223)	2.402*** (0.165)	-0.753*** (0.130)	0.459
Market	Counts	All 15	No	-10.175*** (0.762)	-27.181*** (1.918)	11.508*** (0.805)	0.236*** (0.074)	0.461
Industry	Shares	LASSO 5	No	0.360*** (0.038)	-0.371 (0.574)	0.193 (0.400)	1.697*** (0.313)	0.456
Industry	Counts	LASSO 5	No	-0.811*** (0.122)	-1.916*** (0.198)	1.330*** (0.147)	-0.518*** (0.119)	0.457
Industry	Counts	All 15	No	-2.823*** (0.339)	-8.153*** (0.848)	3.523*** (0.360)	0.078 (0.058)	0.458
Industry	Shares	LASSO 5	Yes	0.042** (0.018)	0.035 (0.026)	-0.088*** (0.025)	-1.582*** (0.562)	0.456
Industry	Counts	LASSO 5	Yes	0.013 (0.014)	-0.185*** (0.039)	0.140*** (0.032)	3.078*** (0.259)	0.455
Industry	Counts	All 15	Yes	0.538*** (0.074)	0.788*** (0.183)	-0.364*** (0.089)	0.412*** (0.125)	0.458

Regressions of log turnover on dispersion H , directional disagreement D , their interaction and price pressure τ (equation (17)), with the full control set: $|r_{i,t}|$, $\ln \text{TO}_{i,t-1}$, $\ln(1 + \text{no. articles}_t)$, R_t^{LS} , VIX_t , TPU_t and $(\text{ask} - \text{bid})/\text{mid}_{i,t}$. First row: narrative measures as in the main text. Other rows: the narrative measures are replaced by the topic-based measures of equations (14)–(16). Exposure: market-wide pooled OLS loadings or sector loadings from model (12). Factor: shares or counts. Topics: five LASSO-selected topics, or the 14 most prominent plus the pooled rest (all 15 topics for stories). Regimes: topic contributions with piecewise-constant coefficients (equation (13)). Stock fixed effects; standard errors clustered by stock in parentheses; $N = 40,572$ stock-days. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table I.5: Control: topic-based measures added to narrative measures

Topic information added				Narrative measures				Within R^2
Exposure	Factor	Topics	Regimes	H	D	$H \times D$	τ	
No alternative measure (main text)				0.418*** (0.028)	1.127*** (0.068)	-0.647*** (0.036)	-0.153 (0.108)	0.460
<i>A. Topics estimated on raw articles ($K = 25$)</i>								
Topic factors	Shares	LASSO 5	No	0.187*** (0.028)	0.572*** (0.067)	-0.353*** (0.036)	0.059 (0.108)	0.471
Topic factors	Counts	LASSO 5	No	0.427*** (0.028)	1.147*** (0.067)	-0.652*** (0.036)	-0.715*** (0.144)	0.462
Market	Counts	LASSO 5	No	0.429*** (0.028)	1.118*** (0.067)	-0.648*** (0.036)	-0.367*** (0.125)	0.463
Market	Counts	Top 15	No	0.419*** (0.028)	1.191*** (0.068)	-0.661*** (0.036)	-1.122*** (0.162)	0.463
Industry	Shares	LASSO 5	No	0.406*** (0.028)	1.116*** (0.068)	-0.639*** (0.036)	-0.225** (0.113)	0.460
Industry	Counts	LASSO 5	No	0.411*** (0.028)	1.080*** (0.068)	-0.628*** (0.036)	-0.170 (0.124)	0.462
Industry	Counts	Top 15	No	0.422*** (0.029)	1.180*** (0.068)	-0.666*** (0.037)	-1.359*** (0.193)	0.461
Industry	Shares	LASSO 5	Yes	0.426*** (0.029)	1.157*** (0.069)	-0.663*** (0.037)	-0.225* (0.116)	0.461
Industry	Counts	LASSO 5	Yes	0.408*** (0.029)	1.147*** (0.068)	-0.642*** (0.036)	-0.706*** (0.120)	0.463
Industry	Counts	Top 15	Yes	0.434*** (0.029)	1.231*** (0.068)	-0.685*** (0.036)	-0.853*** (0.159)	0.462
<i>B. Topics estimated on condensed stories ($K = 15$)</i>								
Topic factors	Shares	LASSO 5	No	0.381*** (0.028)	1.145*** (0.067)	-0.623*** (0.036)	-0.342*** (0.112)	0.473
Topic factors	Counts	LASSO 5	No	0.449*** (0.028)	1.220*** (0.068)	-0.693*** (0.036)	-0.151 (0.138)	0.464
Market	Shares	LASSO 5	No	0.474*** (0.029)	1.286*** (0.070)	-0.736*** (0.037)	-0.332*** (0.111)	0.465
Market	Counts	LASSO 5	No	0.426*** (0.028)	1.198*** (0.067)	-0.677*** (0.036)	-0.488*** (0.141)	0.464
Market	Counts	All 15	No	0.444*** (0.029)	1.379*** (0.071)	-0.739*** (0.038)	-1.359*** (0.167)	0.468
Industry	Shares	LASSO 5	No	0.455*** (0.029)	1.229*** (0.071)	-0.706*** (0.038)	-0.298*** (0.112)	0.463
Industry	Counts	LASSO 5	No	0.422*** (0.028)	1.178*** (0.068)	-0.668*** (0.036)	-0.312** (0.139)	0.463
Industry	Counts	All 15	No	0.423*** (0.029)	1.251*** (0.071)	-0.693*** (0.038)	-1.304*** (0.176)	0.464
Industry	Shares	LASSO 5	Yes	0.379*** (0.029)	1.055*** (0.069)	-0.606*** (0.037)	-0.171 (0.110)	0.461
Industry	Counts	LASSO 5	Yes	0.452*** (0.030)	1.231*** (0.071)	-0.702*** (0.038)	-0.374*** (0.114)	0.462
Industry	Counts	All 15	Yes	0.434*** (0.029)	1.163*** (0.069)	-0.655*** (0.037)	-1.296*** (0.168)	0.465

Regressions of log turnover on the narrative measures of the main text (equation (17)) with the full control set, as in Table I.4. Each row adds topic information: “Topic factors” rows add the five LASSO-selected daily topic factors (shares or counts) as regressors; the other rows add the topic-based H^{topic} , D^{topic} and τ^{topic} of the indicated variant (coefficients not reported). The market-exposure variant with shares is used only in the substitution regressions. Stock fixed effects; standard errors clustered by stock in parentheses; $N = 40,572$ stock-days. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table I.6: Interaction coefficient across control sets

Exposure	Factor	Topics	Regimes	Substitution: topic $H \times D$			Control: narrative $H \times D$		
				Base	+ R^{LS}	Full	Base	+ R^{LS}	Full
Narratives (main text)				-0.590*** (0.037)	-0.608*** (0.037)	-0.647*** (0.036)	-0.590*** (0.037)	-0.608*** (0.037)	-0.647*** (0.036)
<i>A. Topics estimated on raw articles (K = 25)</i>									
Topic factors	Shares	LASSO 5	No	—	—	—	-0.223*** (0.035)	-0.248*** (0.035)	-0.353*** (0.036)
Topic factors	Counts	LASSO 5	No	—	—	—	-0.594*** (0.036)	-0.586*** (0.036)	-0.652*** (0.036)
Market	Shares	LASSO 5	No	0.799*** (0.207)	0.257 (0.208)	2.372*** (0.206)	—	—	—
Market	Counts	LASSO 5	No	5.831*** (0.128)	5.403*** (0.130)	4.923*** (0.126)	-0.570*** (0.036)	-0.591*** (0.036)	-0.648*** (0.036)
Market	Counts	Top 15	No	4.280*** (0.737)	-1.127 (0.759)	3.625*** (0.782)	-0.606*** (0.036)	-0.606*** (0.036)	-0.661*** (0.036)
Industry	Shares	LASSO 5	No	0.666*** (0.125)	0.370*** (0.123)	0.714*** (0.126)	-0.593*** (0.037)	-0.600*** (0.037)	-0.639*** (0.036)
Industry	Counts	LASSO 5	No	3.211*** (0.147)	2.908*** (0.142)	2.613*** (0.134)	-0.558*** (0.036)	-0.579*** (0.036)	-0.628*** (0.036)
Industry	Counts	Top 15	No	1.123*** (0.324)	0.249 (0.336)	0.735** (0.339)	-0.596*** (0.037)	-0.598*** (0.037)	-0.666*** (0.037)
Industry	Shares	LASSO 5	Yes	-0.140*** (0.026)	-0.134*** (0.026)	-0.207*** (0.028)	-0.605*** (0.037)	-0.623*** (0.037)	-0.663*** (0.037)
Industry	Counts	LASSO 5	Yes	-0.145*** (0.028)	-0.272*** (0.030)	-0.291*** (0.030)	-0.552*** (0.036)	-0.602*** (0.037)	-0.642*** (0.036)
Industry	Counts	Top 15	Yes	0.931*** (0.164)	0.851*** (0.164)	0.763*** (0.166)	-0.644*** (0.037)	-0.648*** (0.037)	-0.685*** (0.036)
<i>B. Topics estimated on condensed stories (K = 15)</i>									
Topic factors	Shares	LASSO 5	No	—	—	—	-0.567*** (0.037)	-0.588*** (0.037)	-0.623*** (0.036)
Topic factors	Counts	LASSO 5	No	—	—	—	-0.637*** (0.037)	-0.635*** (0.036)	-0.693*** (0.036)
Market	Shares	LASSO 5	No	11.040*** (1.333)	15.808*** (1.347)	11.244*** (1.348)	-0.644*** (0.038)	-0.658*** (0.038)	-0.736*** (0.037)
Market	Counts	LASSO 5	No	0.297* (0.163)	0.593*** (0.164)	2.402*** (0.165)	-0.628*** (0.036)	-0.641*** (0.036)	-0.677*** (0.036)
Market	Counts	All 15	No	8.692*** (0.780)	5.815*** (0.793)	11.508*** (0.805)	-0.654*** (0.037)	-0.669*** (0.037)	-0.739*** (0.038)
Industry	Shares	LASSO 5	No	-0.146 (0.394)	-0.015 (0.395)	0.193 (0.400)	-0.625*** (0.038)	-0.641*** (0.038)	-0.706*** (0.038)
Industry	Counts	LASSO 5	No	0.392*** (0.146)	0.518*** (0.144)	1.330*** (0.147)	-0.608*** (0.036)	-0.623*** (0.036)	-0.668*** (0.036)
Industry	Counts	All 15	No	2.349*** (0.367)	2.366*** (0.362)	3.523*** (0.360)	-0.601*** (0.037)	-0.612*** (0.037)	-0.693*** (0.038)
Industry	Shares	LASSO 5	Yes	-0.004 (0.024)	-0.029 (0.025)	-0.088*** (0.025)	-0.610*** (0.038)	-0.634*** (0.038)	-0.606*** (0.037)
Industry	Counts	LASSO 5	Yes	0.077*** (0.030)	0.071** (0.030)	0.140*** (0.032)	-0.679*** (0.039)	-0.666*** (0.038)	-0.702*** (0.038)
Industry	Counts	All 15	Yes	-0.131 (0.084)	-0.433*** (0.085)	-0.364*** (0.089)	-0.553*** (0.037)	-0.574*** (0.037)	-0.655*** (0.037)

Coefficient on $H \times D$ in equation (17). Substitution: topic-based interaction, with topic-based measures replacing the narrative ones (as in Table I.4). Control: narrative interaction, with topic information added (as in Table I.5). Control sets: Base ($|r_{i,t}|$, $\ln \text{TO}_{i,t-1}$, $\ln(1 + \text{no. articles}_t)$); + R^{LS} (Base and the tariff long-short portfolio return); Full (+ R^{LS} , VIX_t , TPU_t and the relative bid-ask spread). First row: narrative interaction without topic information, the benchmark for both blocks. Stock fixed effects; standard errors clustered by stock in parentheses; $N = 40,572$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

J Theoretical Model: Narrative Cacophony and Volume

This section bears on modeling trading behaviour, taking narratives as given and focusing on the effect of disagreement. I show, first, that the volume-dampening effect of cacophony I document cannot be rationalized under a standard Differences-of-Opinion framework in the style of [Kandel and Pearson \(1995\)](#), which instead implies that cacophony should have a non-negative effect on trade. I then propose a modification of the framework: drawing on insights from the ambiguity literature, I add an cacophony-sensitivity term, which recovers the desired volume-dampening effect. (If agents are insensitive to narrative cacophony, the standard set-up of [Kandel and Pearson \(1995\)](#), with all the classical results, obtains.)

J.1 Setup

There is a single risky asset, in unit net supply, with dividends

$$d_{t+1} = \bar{d} + \mu_{t+1} + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma_d^2),$$

with $\mu_{t+1} = \mu_t + \eta_{\mu_t}$, $\eta_{\mu_t} \sim \mathcal{N}(0, \sigma_\mu^2)$. There are K narratives and a unit mass of investors uniformly distributed across K types; type k believes only in narrative k , with each narrative k interpreting public information in the time-series,²² as captured by filtration $\mathbb{F}$. In other words, $\mathbb{F}_t$ is a publicly observable filtration, which each investor type k interprets via ϕ_{kt} inducing cross-sectional beliefs $\phi_t = (\phi_{1t}, \dots, \phi_{Kt})' \in \mathbb{R}^K$ at time t over the latent state:

$$\phi_{kt} = \mathbb{E}_k[\mu_t + \varepsilon_t] = \mathbb{E}_k[\mu_t]$$

where $\mathbb{E}_k[\eta_{\mu_{t+s}} | \phi_t] = \mathbb{E}_k[\varepsilon_{t+s} | \phi_t] = 0$ is assumed for $s \geq 0$ so that

$$\mathbb{E}_k[d_{t+1} | \mathbb{F}_t] = \mathbb{E}_k[d_{t+1} | \phi_t] = \bar{d} + \mathbb{E}_k[\mu_{t+1} | \phi_{kt}] = \bar{d} + \phi_{kt}.$$

Assume the narratives follow a Gaussian random walk, too,²³ with

$$\phi_t = \phi_{t-1} + F_t, \quad F_t \sim \mathcal{N}(0, \Sigma_t).$$

These F_t interpret the latest public information news shock, as captured by filtration $\mathbb{F}_t$. In the empirical part, the realizations of the “daily narrative factor” are exactly these evolutions F . Investors have CARA utility with risk aversion γ , live forever, and face gross risk-free rate $1 + r_f$ on a risk-free asset.

²²Underlying all this is a $(K + 1) \times T$ data set.

²³The random walk structure can be viewed as a reduced-form description of Bayesian updating under persistent fundamentals.

Proposition 1. The equilibrium asset allocations x_{kt} for investors of type k at time t , risky asset returns r_t^e and prices p_t , and turnover from period $t-1$ to t , $\mathcal{V}_t$, are given by:

$$p_t = A + B'\phi_t \quad \text{where} \quad A = \frac{\bar{d} - \gamma V}{r_f}, \quad B = \frac{1}{Kr_f} \mathbf{1}, \quad \text{and} \quad V = \sigma_d^2 + \sigma_\mu^2 + \frac{c}{K^2} \quad (18)$$

$$r_t^e = \frac{p_t + d_t - p_{t-1}}{p_{t-1}} = \frac{B'F_t}{p_{t-1}} + \frac{d_t}{p_{t-1}} \quad (19)$$

$$x_{k,t} = 1 + \frac{1}{\gamma V} (\phi_{k,t} - \frac{1}{K} \sum_{k'} \phi_{k',t}) \quad (20)$$

$$\mathcal{V}_t := \frac{1}{2} \sum_{k=1}^K \frac{1}{K} |x_{k,t} - x_{k,t-1}| \quad (21)$$

$$= \frac{1}{2K\gamma V} \sum_{k=1}^K |\phi_{k,t} - \phi_{k,t-1} - \frac{1}{K} \sum_{k'=1}^K (\phi_{k',t} - \phi_{k',t-1})| \quad (22)$$

$$= \frac{1}{2K\gamma V} \sum_{k=1}^K |F_{k,t} - \frac{1}{K} \sum_{k'=1}^K F_{k',t}| \quad (23)$$

where K is the number of narratives, as above.

Proof. Equilibrium solved in section J.3. □

In equilibrium, investors hold the market portfolio, up to a tilt introduced by the departure of their narrative from the average forecast. Prices and hence returns, meanwhile, depend only on average forecasts. Introduce the following measures of narrative contents (τ) and disagreement (H, D) and cacophony:

Symbol	Definition
total narrative-implied price-pressure	$\tau_t = \sum_k F_{kt}/K = \ F_{kt}/K\ _1$
directional disagreement	$D_t = 1 - \frac{ \sum_k F_{kt}/K }{\tau_t} \in [0, 1]$
entropy	$H_t = -\sum_k p_k \ln p_k, \quad p_k = \frac{ F_{kt}/K }{\tau_t}$
narrative cacophony	$H_t \times D_t$

Remark 1. It is important to note that in the empirical part, the factors F_{kt}^{factor} – because they are built from the tariff-price-impact decomposition – already implicitly take into account the share of the population that finds the narrative compelling. Thus, to correctly

interpret the results and their correspondence with the empirical part, it is helpful to keep in mind that

$$F_{kt}^{\text{factor}} = F_{kt}^{\text{theory}} / K.$$

Notice that τ, H, D are equal: τ already is implicitly re-scaled by construction, and H, D do not require re-scaling.

J.1.1 Standard Differences-of-Opinion Setting

This section derives the sign of the cross-effect of dispersion H and directional disagreement D on turnover, holding fixed aggregate narrative pressure τ , in a way consistent with the standard Differences-of-Opinion Literature. In what follows, I first establish $\partial^2 \mathcal{V} / \partial H \partial D \geq 0$ on equal-magnitude narrative shocks (as in the main text of the paper). Then, I will pass to a generalization in which this assumption is relaxed and perturbations are given by Pigou-Dalton transfers (Pigou, 1912; Dalton, 1920). I begin with the volume expression from 1:

$$\mathcal{V}_t = \frac{1}{2K\gamma V} T_t, \quad T_t := \sum_{k=1}^K |F_{kt} - \bar{F}_t|, \quad \bar{F}_t := \frac{1}{K} \sum_{k=1}^K F_{kt}, \quad (24)$$

which is exactly the K -type version of the Kandel and Pearson (1995) framework (where beliefs happen to be informed by narratives).

Fix a date with $F \neq 0$ (so $\tau > 0$); I omit the time subscript for notational convenience. Write $s := \text{sgn}(\bar{F})$ and $\tilde{F}_k := sF_k$, so that the consensus revision is $\tilde{\bar{F}} = |\bar{F}| = (1 - D)\tau \geq 0$. (s is useful only for notational shorthand; nothing below depends on this parameter.)

Definition J.1 (Consensus side, leaders, followers). Suppose $D < 1$ (so that $s \neq 0$). Narrative k is on the *consensus side* if $\tilde{F}_k > 0$, *dissenting* if $\tilde{F}_k < 0$, and *dormant* if $F_k = 0$. A consensus-side narrative is a *leader* if $\tilde{F}_k \geq |\bar{F}|$ (it sets its price revision at least as far as the consensus, in the same direction as the consensus) and a *follower* if $0 < \tilde{F}_k < |\bar{F}|$. Define the *effective number of consensus-carrying narratives*

$$c(F) := \sum_{k=1}^K \min\left(\frac{\tilde{F}_k^+}{|\bar{F}|}, 1\right) = \#\{\text{leaders}\} + \sum_{\text{followers}} \frac{\tilde{F}_k}{|\bar{F}|},$$

where $x^+ = \max(x, 0)$. Thus, c counts the number of leaders; the degree to which followers contribute to the consensus (i.e., their revision as a fraction of the consensus revision); and does not count dissenting and dormant narratives.

Lemma 1 (Volume identity). For every configuration F with $D < 1$,

$$T = \tau \left[2(K - c) - D(K - 2c) \right] = K\tau(2 - D) - 2(1 - D)\tau c, \quad (25)$$

with $c \in [1, K - 1]$ when $D \in (0, 1)$ and $c \in [1, K]$ when $D = 0$. When $D = 1$, $T = K\tau$ for every configuration.

Proof. In what follows, the set of Dissenters includes Dormant narratives as well. For $D < 1$,

$$\begin{aligned} T &= \sum_{k \in K} |F_k - \bar{F}| \\ &= \sum_{k \in \text{Leaders}} (|F_k| - |\bar{F}|) - \sum_{k \in \text{Followers}} (|F_k| - |\bar{F}|) + \sum_{k \in \text{Dissenters}} (|F_k| + \bar{F}) \\ &= \sum_{k \in \text{Lead}} |F_k| - \sum_{k \in \text{Follow}} |F_k| + \sum_{k \in \text{Diss.}} |F_k| + |\bar{F}|(\# \text{Follow} + \# \text{Diss.} - \# \text{Lead}) \\ &= K\tau - 2 \sum_{k \in \text{Follow}} |F_k| + (1 - D)\tau K - 2|\bar{F}|\# \text{Lead} \\ &= K\tau(2 - D) - 2(1 - D)\tau \left(\# \text{Lead} + \sum_{k \in \text{Follow}} \frac{F_k}{|\bar{F}|} \right) \\ &= K\tau(2 - D) - 2(1 - D)\tau c \end{aligned}$$

where $c \geq 1$ as there must be at least one leader (from $|\bar{F}| > 0$). $D > 0$ would imply there is at least one dissenter $\tilde{F}_k < 0$, so $c \in [1, K - 1]$, and $D = 0$ means $c \in [1, K]$. And if $D = 1$, $\bar{F} = 0$, so $T = \sum_k |F_k| = K\tau$. □

Notice that the effects of the dispersion of consensus, holding constant τ and D , are bounded:

Corollary 1 (Bounds on dispersion). For every configuration with $D \in (0, 1]$,

$$K\tau - (K - 2)(1 - D)\tau \leq T \leq K\tau + (K - 2)(1 - D)\tau.$$

The band size is decreasing in D , and collapses to the point $K\tau$ at $D = 1$.

Proof. Evaluate (25) at $c = 1$ and $c = K - 1$ for $D \in (0, 1)$, and at $D = 1$ separately. □

Narrative Dispersion H depends only on c , but there is no one-to-one mapping. So Corollary 1 is useful because it bounds any effect of dispersion on volume – at any level of H , whatever its relationship with c – by $2(K - 2)(1 - D)\tau$, and forces it to vanish at $D = 1$.

J.1.2 Equal-magnitude Narrative Shocks

Definition J.2 (Equal-magnitude narrative shocks). Narrative shocks are of *equal magnitude* if the $n \in \{1, \dots, K\}$ active narratives all have $|F_k| = K\tau/n$, with $n_N \leq n/2$ of them dissenting and $n_P = n - n_N$ on the consensus side. On this set

$$H = \log n, \quad D = \frac{2n_N}{n}, \quad c = n_P = n\left(1 - \frac{D}{2}\right) \quad (D < 1),$$

and H and D uniquely pin down c . More concretely, $(H, D) \mapsto (n, n_N)$ is a bijection and the map is inverted by $n = e^H$, $n_N = e^H D/2$.

For equal-magnitude narrative shocks and $D < 1$, $c = n_P$ because every consensus-side narrative is a leader: $K\tau/n \geq (1 - D)\tau$ since $n \leq K$ and $D \geq 0$. (At $D = 1$, $T = K\tau$ by Lemma 1, which is what (26) below gives.)

Proposition 2 (Non-negative interaction in (H, D)). On equal-magnitude narrative shock configurations, volume is

$$T(H, D) = \tau(2 - D)(K - e^H(1 - D)) = K\tau(2 - D)\left(1 - \frac{e^H}{K}(1 - D)\right), \quad (26)$$

and, holding τ fixed,

$$\begin{aligned} \frac{\partial T}{\partial H} &= -\tau e^H(2 - D)(1 - D) \leq 0, \\ \frac{\partial^2 T}{\partial H \partial D} &= \tau e^H(3 - 2D) > 0, \quad \frac{\partial^2 \log T}{\partial H \partial D} = \frac{\frac{e^H}{K}}{\left(1 - \frac{e^H}{K}(1 - D)\right)^2} > 0, \end{aligned}$$

The same partial derivative signs hold for $\mathcal{V} = T/(2K\gamma V)$.

Proof. Substitute $c = e^H(1 - D/2)$ into (??): $2K - n(2 - D) - DK + Dn(2 - D) = (2 - D)(K - n(1 - D))$. Differentiating (26) with respect to H gives $\frac{\partial T}{\partial H} = -\tau e^H(2 - D)(1 - D)$; differentiating further with respect to D , $\frac{\partial^2 T}{\partial H \partial D} = -\tau e^H \partial_D[(2 - D)(1 - D)] = \tau e^H(3 - 2D)$. For the log, $\frac{\partial \log T}{\partial H} = \frac{-\tau e^H(1 - D)(2 - D)}{T} = 1 - \frac{1}{1 - \frac{e^H}{K}(1 - D)}$ so $\frac{\partial^2 \log T}{\partial H \partial D} = \frac{\frac{e^H}{K}}{(1 - \frac{e^H}{K}(1 - D))^2}$. As $\mathcal{V} = T/(2K\gamma V)$, $\partial^2 \mathcal{V}/\partial H \partial D$ adopts the sign of $\partial^2 T/\partial H \partial D$ $\square$

J.1.3 Non-equal-magnitude narrative shocks

Now, I relax the assumption that narrative shocks must be equal in magnitude, but differences in narrative-shock allocations are given only by Pigou-Dalton transfers: redistributive transfers of narrative shocks on the same side of the consensus. Under this

assumption, I'll show that, at fixed (τ, D) , spreading a given amount of consensus-side revision over more narratives raises H , raises c , and lowers volume.

Proposition 3 (Pigou-Dalton transfers, c, H and T). Fix a configuration with $|\bar{F}| > 0, D < 1$. Let i, j be two narratives on the same side (both consensus-side or dormant, or both dissenting; the boundary of a dormant narrative can be included in both cases) with $|\tilde{F}_i| > |\tilde{F}_j| \geq 0$. Transferring a “small” amount of weight from F_i to F_j will weakly increase c and H , and weakly decrease T .

Let $0 < \delta \leq (|\tilde{F}_i| - |\tilde{F}_j|)/2$. The side-preserving Pigou-Dalton transfer F' moves magnitude δ from narrative i to narrative j without any narratives changing sides: $|\tilde{F}'_i| = |\tilde{F}_i| - \delta$, $|\tilde{F}'_j| = |\tilde{F}_j| + \delta$, $\text{sgn } \tilde{F}'_i = \text{sgn } \tilde{F}_i$, $\text{sgn } \tilde{F}'_j = \text{sgn } \tilde{F}_j$ (a dormant recipient takes the donor's sign), and $\tilde{F}'_k = \tilde{F}_k$ otherwise. It satisfies:

- (i) $\tau' = \tau$, $\bar{F}' = \bar{F}$, $D' = D$;
- (ii) $H' > H$;
- (iii) if i, j are on the consensus side, $c' \geq c$ and $T' - T = -2(1 - D)\tau(c' - c) \leq 0$; if they are on the dissenting side, $c' = c$ and $T' = T$.

Proof. (i) Because $|\tilde{F}_i| - \delta \geq |\tilde{F}_j| + \delta \geq 0$ and signs are preserved, $\sum_k \tilde{F}_k$ and $\sum_k |F_k|$ are unchanged; so τ , $\bar{F}$ and D are the same. (ii) The vector $(|\tilde{F}'_k|)_k$ is obtained from $(|\tilde{F}_k|)_k$ by a Pigou-Dalton transfer, so it is strictly majorized by it. As Shannon entropy is strictly Schur-concave, it is increasing under majorization: $H' > H$.

(iii) On the consensus side, as $x \mapsto \min(x, |\bar{F}|)$ is concave, so is the finite sum $\sum_k \min(\tilde{F}_k^+, |\bar{F}|)$, and hence c itself. From concavity it follows that c weakly increases under a Pigou-Dalton transfer.²⁴ Thus $c' \geq c$, and, from (??), it follows that $T' - T = -2(1 - D)\tau(c' - c) \leq 0$.

As for the dissenting side the terms $\min(\tilde{F}_k^-, |\bar{F}|)$ are zero before and after, so c and T are unchanged. $\square$

Proposition 4 (DOO: c, D and Volume). Under the assumptions of the Kandel and Pearson (1995) model, holding τ fixed:

- (i) At $D = 1$, volume equals $K\tau$ for every configuration: c has no effect.
- (ii) For $D \in (0, 1)$, volume (25) satisfies

$$\frac{\partial T}{\partial c} = -2(1 - D)\tau \leq 0, \quad \frac{\partial^2 T}{\partial c \partial D} = 2\tau > 0, \quad \frac{\partial^2 \log T}{\partial c \partial D} = \frac{2K\tau^2}{T^2} > 0.$$

²⁴For a concave f and $x > y, 0 < \delta < \frac{x-y}{2}$, $f(x - \delta) + f(y + \delta) \geq f(x) + f(y)$ follows from $\frac{f(y+\delta)-f(y)}{\delta} \geq \frac{f(x)-f(y)}{x-y} \geq \frac{f(x)-f(x-\delta)}{\delta}$. For $\delta = \frac{x-y}{2}$, the desired inequality is satisfied by the usual definition of concavity: $f(\frac{x+y}{2}) \geq \frac{1}{2}f(x) + \frac{1}{2}f(y)$.

(iii) Any Pigou-Dalton change in narrative shocks lowers volume by $2(1 - D)\tau \Delta c$; the effect is bounded by $2(K - 2)(1 - D)\tau$ and shrinks linearly to zero in D .

Proof. (i) is identical to Lemma 1. (ii) The computations of $\frac{\partial T}{\partial c}$ and $\frac{\partial^2 T}{\partial c \partial D}$ are immediate, and

$$\begin{aligned}\frac{\partial \log T}{\partial c} &= \frac{-2(1 - D)\tau}{T} \\ \frac{\partial^2 \log T}{\partial c \partial D} &= \frac{2\tau}{T} + \frac{2(1 - D)\tau}{T^2}(2\tau c - K\tau) \\ &= \frac{2K\tau^2}{T^2}\end{aligned}$$

(iii) is just Lemma 3(iii) combined with Corollary 1. □

The intuition is as follows. When narratives are unanimous or close to unanimous ($D \rightarrow 0$), consensus is large and the geometry of the consensus is the main driver of trade: if all narratives move in exactly the same way, there is no trade; if all of the narrative revisions come from a single narrative, its adherents trade against the rest of the market. But when narratives cancel out ($D = 1$), there is no price movement at all, every agent can trade their own revision, and volume is completely independent of the consensus geometry (cf Lemma 1) for lack thereof.

Corollary 2. From Propositions 3 and 4, it follows that, in a Kandel and Pearson setting, a Pigou-Dalton transformation of narratives will increase c in such a way that H increases and $\frac{\partial^2 T}{\partial c \partial D} \geq 0$.

Remark 2 (Interpretation and Limitations). H is not a sufficient statistic for volume on arbitrary narrative shock configurations: two configurations with the same (τ, H, D) can have different c . Fully generic claims can be made using c, D , as in Proposition ??, or – in the language of H, D – in equal-magnitude narrative shocks or in the case of consensus-preserving Pigou-Dalton transfers.

The reason it is not possible to make fully general statements for arbitrary comparisons of narrative shock configurations in the language of H and D has to do with the possibility of an arbitrary transfer changing the consensus level itself: if a “transfer” is strong enough as to transform a leader into a follower (because the threshold $|\bar{F}|$ that defines c moves with D), the sign of the cross-partial can fail because the change in H then corresponds also to a change in too many other parameters. (This is a boundary effect whose magnitude is bounded by the usual $2(K - 2)(1 - D)\tau$, and vanishes as $D \rightarrow 1$.) This is exactly the case accounted-for by consensus-preserving Pigou-Dalton transfers.

J.2 Cacophony, ambiguity, and a negative interaction

Given that the notion of narrative cacophony has conceptual analogues in the ambiguity literature – in particular, that narrative cacophony can be interpreted as the aggregate-level analogue to ambiguity in priors – it is not surprising that one of the most parsimonious ways to recover a negative interaction term $\partial^2 V / \partial H \partial D < 0$ is by borrowing some modeling choices from the ambiguity literature (especially the smooth ambiguity model proposed in [Klibanoff et al. \(2005\)](#) and applied to investment decisions in [Maccheroni et al. \(2013\)](#)).

Sensitivity to narrative cacophony. Let investors' common perceived variance of next-period payoffs be

$$V_t = V \Psi(\mathcal{A}_t), \quad \Psi \in C^2, \quad \Psi(0) = 1, \quad \Psi' \geq 0, \quad (27)$$

where $V = \sigma_d^2 + \sigma_\mu^2 + \text{Var}(\bar{F}_{t+1})$ is the variance under the reference model (as in Proposition 1) and $\mathcal{A}_t \geq 0$ is an index of the narrative cacophony at date- t , and Ψ tracks investors' sensitivity to narrative cacophony. With $\Psi \equiv 1$ the model recovers the standard [Kandel and Pearson \(1995\)](#) set-up.

Lemma 2 (Equilibrium with sensitivity to narrative cacophony). With V_t given by (27), equilibrium holdings are $x_{kt} = 1 + (\phi_{kt} - \bar{\phi}_t)/(\gamma V_t)$ and the price is $p_t = a_t + \bar{\phi}_t/r_f$, where a_t is common to all types and depends only on public information. Volume from $t - 1$ to t is

$$\mathcal{V}_t = \frac{1}{2K\gamma} \sum_{k=1}^K \left| \frac{F_{kt} - \bar{F}_t}{V_t} + g_{k,t-1} \left(\frac{1}{V_t} - \frac{1}{V_{t-1}} \right) \right|, \quad g_{k,t-1} = \phi_{k,t-1} - \bar{\phi}_{t-1},$$

and its *narrative-disagreement-driven component*, the volume generated by the date- t revisions at the date- t sensitivity to narrative cacophony, is

$$\mathcal{V}_t^N := \frac{T_t}{2K\gamma V \Psi(\mathcal{A}_t)}. \quad (28)$$

$\mathcal{V}_t = \mathcal{V}_t^N$ whenever $\Psi(\mathcal{A}_t) = \Psi(\mathcal{A}_{t-1})$.

Proof. The derivation is essentially identical to the original set-up (cf s. J.3). $\square$

The second term in $\mathcal{V}_t$ is a rebalancing of pre-existing tilts $g_{k,t-1}$ caused by a change in perceived risk; it depends on the amount of past disagreement, not on the date- t configuration, and is not what the measures (H_t, D_t) are designed to capture. The results

below concern $\mathcal{V}_t^N$: the amount of volume explainable by (contemporaneous) narrative disagreement.²⁵

Assumption 1 (Narrative Cacophony index). $\mathcal{A} = \mathcal{A}(H, D)$ is continuous, non-decreasing in each argument, and

- (A1) $\mathcal{A}(H, 0) = 0$ for all H : if all active narratives agree on the direction of the news, there is no narrative cacophony, however many narratives there are;
- (A2) $\mathcal{A}(0, D) = 0$ for all D : if a single narrative carries the news, there is no narrative cacophony;
- (A3) $\mathcal{A}$ has the product form $\mathcal{A} = a(H) D$ with $a(0) = 0$, $a' > 0$.

One appealing, and perhaps simplest, choice is $a(H) = (e^H - 1)/K$ and hence $\mathcal{A} = \frac{(e^H - 1)D}{K}$. That is, the effective number of different ways to interpret the news (in excess of the first) multiplied by their directional disagreement, relative to the size of the narrative universe.²⁶

(A1)-(A2) are the substantive assumptions; (A3) proposes a simple functional form satisfying them for tractability. A day is interpretationally complex when there are many (effective) narratives with different directional implications for the asset's price. In other words, a day is interpretationally complex exactly when the narrative environment is cacophonous.

Proposition 5 (Sign of the interaction with sensitivity to narrative cacophony). Consider narrative-disagreement-attributable volume $\mathcal{V}^N$, with Ψ as in (27) and $\mathcal{A}$ as in Assumption 1. Define the elasticity of perceived sensitivity to narrative cacophony with respect to the narrative cacophony index, $\varepsilon_\Psi(\mathcal{A}) := \mathcal{A} \frac{d \log \Psi}{d \mathcal{A}} = \frac{d \log \Psi}{d \log \mathcal{A}}$.

In general, as long as $\partial_H \mathcal{V}^N$ is well-defined, holding τ fixed,

$$\frac{\partial^2 \log \mathcal{V}^N}{\partial H \partial D} = \underbrace{\frac{\partial^2_{HD} T}{\text{à la Kandel-Pearson}}}_{\text{à la Kandel-Pearson}} - \underbrace{a'(H) \varepsilon'_\Psi(\mathcal{A})}_{\text{sensitivity to narrative cacophony}}. \quad (29)$$

²⁵ $\mathcal{V}_t^N = \mathcal{V}_t$ conditional on the ambiguity state not changing between $t - 1$ and t , or in the one-shot setting in which investors start at the market portfolio with common priors (so that $g_{k,t-1} = 0$).

²⁶ The proposed $\mathcal{A}$ also has a natural interpretation on equal-magnitude narrative shock configurations: $(e^H - 1)D/K = (n - 1) \cdot (2n_N/n)/K = \frac{2n_N}{K} \cdot \frac{n-1}{n}$, approximately twice the dissenting share of the narrative universe. In this special case, a day is interpretationally complex exactly when many distinct narratives contradict the direction in which the price is moving.

And, on equal-magnitude narrative configurations, still holding τ fixed,

$$\frac{\partial^2 \log \mathcal{V}^N}{\partial H \partial D} = \underbrace{\frac{\frac{e^H}{K}}{(1 - \frac{e^H}{K}(1 - D))^2}}_{\text{Kandel-Pearson, } \geq 0} - \underbrace{a'(H) \varepsilon'_\Psi(\mathcal{A})}_{\text{narrative cacophony} > 0} \quad (30)$$

In general, the interaction is negative if $a'(H) \varepsilon'_\Psi(\mathcal{A})$ is sufficiently large. For equal-magnitude narrative configurations in particular, this is given by

$$a'(H) \varepsilon'_\Psi(\mathcal{A}) > \frac{\frac{e^H}{K}}{(1 - \frac{e^H}{K}(1 - D))^2}. \quad (31)$$

Proof. From (28), $\log \mathcal{V}^N = \log T - \log \Psi(\mathcal{A}(H, D)) - \log(2K\gamma V)$. For the second term, with $\mathcal{A} = a(H)D$,

$$\begin{aligned} \partial_H \log \Psi(\mathcal{A}) &= (\log \Psi)'(\mathcal{A}) a'(H) D, \\ \partial_D \partial_H \log \Psi(\mathcal{A}) &= a'(H) [(\log \Psi)''(\mathcal{A}) a(H) D + (\log \Psi)'(\mathcal{A})] \\ &= a'(H) \frac{d}{d\mathcal{A}} [\mathcal{A} (\log \Psi)'(\mathcal{A})] \\ &= a'(H) \frac{d}{d\mathcal{A}} \varepsilon_\Psi(\mathcal{A}) \end{aligned}$$

□

Condition (31) implies that the elasticity of sensitivity to narrative cacophony with respect to narrative cacophony must increase with cacophony fast enough to overcome the (mechanical) Kandel–Pearson term. The log-linear specification makes this a single threshold on the ambiguity-aversion parameter. With an explicit choice of Ψ and maintaining the equal-magnitude specifications, a closed-form expression for the desired threshold can be obtained.

Corollary 3 (Explicit threshold). Let $\Psi(\mathcal{A}) = e^{\theta \mathcal{A}}$ with $\theta \geq 0$ and $\mathcal{A} = (e^H - 1)D/K$. Then on equal-magnitude configurations

$$\frac{\partial^2 \log \mathcal{V}^N}{\partial H \partial D} = \frac{e^H}{K} [\theta^*(H, D) - \theta], \quad \theta^*(H, D) := \frac{1}{(1 - \frac{e^H}{K}(1 - D))^2} = \left(\frac{K}{K - (n_P - n_N)} \right)^2,$$

so the interaction is negative if and only if $\theta > \theta^*(H, D)$. Equivalently, at a given $\theta > 1$ the interaction is negative exactly on configurations whose net consensus majority is small relative to the narrative universe:

$$\frac{\partial^2 \log \mathcal{V}^N}{\partial H \partial D} < 0 \iff \frac{n_P - n_N}{K} < 1 - \theta^{-1/2}.$$

Proof. $\varepsilon_\Psi(\mathcal{A}) = \theta \mathcal{A}$, so $\varepsilon'_\Psi = \theta$, and $a'(H) = e^H/K$; substitute in (30) to get $\frac{e^H}{K}/(1 - \frac{e^H}{K}(1 - D))^2 - \frac{e^H}{K}\theta$. For the count form use $\frac{e^H}{K}(1 - D) = (n - 2n_N)/K = (n_P - n_N)/K$. The final equivalence follows from the inequality $\theta > (1 - \frac{e^H}{K}(1 - D))^{-2}$. $\square$

J.3 Derivation of Equilibrium Prices and Quantities

In the following I derive the equilibrium prices p_t and allocations x_{kt} as presented in Proposition 1.

Proof. Each investor k chooses their share allocation x_{kt} to maximize the expected utility of next period's wealth $W_{k,t+1}$. (Under CARA utility and Gaussian random walk beliefs, an infinitely-lived investor's dynamic programming problem collapses mathematically into a sequence of myopic single-period optimizations: the random walks eliminate intertemporal hedging, and the CARA structure rules out wealth effects. So, the long-horizon problem with a consumption stream admits a one-period-at-a-time solution, up to rescaling the risk-aversion coefficient γ by $1/r_f$.)

Next period wealth is given by

$$W_{k,t+1} = W_{kt}(1 + r_f) + x_{kt}Q_{t+1}$$

where Q captures dollar returns (per unit of asset)

$$Q_{t+1} = p_{t+1} + d_{t+1} - (1 + r_f)p_t$$

is the excess dollar return per share, and I conjecture affine prices

$$p_t = a + b'\bar{F}_t.$$

Then

$$\begin{aligned} Q_{t+1} &= p_{t+1} + d_{t+1} - (1 + r_f)p_t \\ &= A + B\bar{\phi}_t + \bar{d} + \mu_{t+1} + \varepsilon_{t+1} - (1 + r_f)(a + b\bar{\phi}_t) \\ \mathbb{E}_{kt}[Q_{k,t+1}] &= \bar{d} + \phi_{kt} - r_f a - r_f b\bar{\phi}_t \\ \text{var}_{kt}(Q_{kt}) &= \text{var}_{kt}(\mu_{t+1} + \varepsilon_{t+1} + bF_{t+1}^-) = \sigma_d^2 + \sigma_\mu^2 + \frac{1}{K^2}1'\Sigma_{t+1}1 = \sigma_d^2 + \sigma_\mu^2 + \frac{c}{K^2} \end{aligned}$$

Under CARA utility ($U(W) = -e^{-\gamma W}$) and normally distributed returns, maximizing expected utility is mathematically equivalent to maximizing the Mean-Variance criterion:

$$\max_{x_{kt}} \left\{ \mathbb{E}_{kt}[W_{k,t+1}] - \frac{\gamma}{2} \text{var}_{kt}(W_{k,t+1}) \right\}$$

Then, given that

$$V := \text{var}_{kt}(W_{k,t+1}) = \text{var}_{kt}(\mu_{t+1} + \varepsilon_{t+1} + B\bar{F}_{t+1}) = \sigma_d^2 + \sigma_\mu^2 + \frac{1}{K^2}1'\Sigma_{t+1}1 = \sigma_d^2 + \sigma_\mu^2 + \frac{c}{K^2},$$

optimal allocations are:

$$x_{kt}^* = \frac{\mathbb{E}_k[Q_{t+1}]}{\gamma V}.$$

The market clearing condition $\sum_k \frac{1}{K} x_{kt}^* = 1$ implies

$$1 = \frac{1}{K} \sum_{k=1}^K \frac{\mathbb{E}_k[Q_{t+1}]}{\gamma V} \quad (32)$$

$$= \frac{1}{K} \sum_{k=1}^K \frac{\bar{d} + \phi_{kt} - r_f a - r_f b \bar{\phi}_t}{\gamma V} \quad (33)$$

so

$$a = \frac{\bar{d} - \gamma V}{r_f} \quad b = \frac{1}{r_f}$$

and thus

$$p_t = \frac{\bar{d} - \gamma V}{r_f} + \frac{1}{Kr_f} 1' F_t \quad x_{kt}^* = \frac{\mathbb{E}_{kt}[Q_{t+1}]}{\gamma V} = 1 + \frac{\phi_{kt} - \bar{\phi}_t}{\gamma V}.$$

□

Do prices incorporate anticipated future prices? An alternative derivation of the equilibrium price. The following bypasses the conjecture that the price must be affine in $\bar{\phi}_t$.

For $\bar{\mathbb{E}}_t[\cdot] = \frac{1}{K} \sum_k \mathbb{E}_{kt}[\cdot]$,

$$\begin{aligned} p_t &= \frac{1}{1+r_f} (\bar{\mathbb{E}}_t[d_{t+1} + p_{t+1}] - \bar{\mathbb{E}}_t[Q_{t+1}]) \\ &= \frac{1}{1+r_f} (\bar{\mathbb{E}}_t[d_{t+1} + p_{t+1}] - \gamma V) \quad \text{follows from (32)} \\ p_t &= \sum_{s=1}^T \frac{\bar{\mathbb{E}}_t[d_{t+s}] - \gamma V}{(1+r_f)^s} + \frac{\bar{\mathbb{E}}_t[p_{t+T}]}{(1+r_f)^T} \end{aligned}$$

As beliefs follow a random walk ($\bar{\mathbb{E}}_t[\bar{\phi}_{t+s}] = \bar{\phi}_t$), taking the limit as $T \rightarrow +\infty$ and

computing the geometric sum yields

$$\begin{aligned}
 p_t &= \sum_{s=1}^{+\infty} \frac{\bar{d} + \bar{\phi}_t - \gamma V}{(1 + r_f)^s} \\
 &= \frac{\bar{d} - \gamma V}{r_f} + \frac{1}{r_f} \bar{\phi}_t \\
 &= \frac{\bar{d} - \gamma V}{r_f} + \frac{1}{Kr_f} 1' \phi_t
 \end{aligned}$$

Underlying the above argument are the following usual assumptions:

1. The standard bubble-avoiding assumption $\lim_{T \rightarrow +\infty} \frac{\mathbb{E}_t[p_{t+T}]}{(1 + r_f)^T} = 0$.
2. The Law of Iterated Expectations for the average belief: $\bar{\mathbb{E}}_t[\bar{\mathbb{E}}_{t+1}[\cdot]] = \bar{\mathbb{E}}_t$.

K Story Structure Results & Narrative Regime-Intensity

In this section, I examine the internal structure of stories and narratives. The goal is to establish that narratives are meaningful objects with desirable properties. A decomposition of stories' constituent statements into realized events and hypothesized predictions, and each statement into six informational dimensions (who, what, where, when, why, and how) informs the subsequent analysis.

First, I consider event and prediction similarity within and across narrative communities, and find that narrative membership is strongly explained by the similarity of stories' predictions, and not by stories' events. Indeed, narrative membership significantly increases the similarity of stories' predictions, while the stories' events' similarities remain essentially unchanged. Second, I document that the six 5W1H structural dimensions are starkly heterogeneous in their explanatory power of events and predictions. Indeed, the "plot" dimensions (*who*, *what*) drive event convergence while the "mechanism" dimensions (*why*, *how*) is salient for prediction convergence. This serves as an important validation of the meaningfulness of story structure: hypothesized predictions are structurally different from realized events. Third, motivated by the finding that narratives cluster around predictions, I consider the relationship between the similarity of predictions made within a narrative on a given day and the informativeness of the narrative regime. I show that informativeness is inversely related to the coherence of within-narrative predictions: on a given day, the market is actively pricing the narratives which entertain multiple predictions; meanwhile, an anodyne consensus betrays the fact that the narrative has already been priced by the market and hence reduced to banalities.

K.1 Story Structure & Decomposition

Recall that a story is a chronologically-ordered finite list of statements. As per Figure K.1, each statement can bear on the past (a realized *event*) or on the future (a hypothesized *prediction*). Each statement also encodes information along six dimensions: *who*, *what*, *where*, *when*, *why*, and *how*.²⁷ Thus, it is natural to refer to specific informational dimensions of a fact: for instance, f_{what} and f_{when} capture the *plot*, while f_{why} and f_{how} provide the *mechanism*.

²⁷The statement may express, implicitly or explicitly, the information contained in one or more of these dimensions; the dimensions offer a structured semantic description of the fact's informational contents.

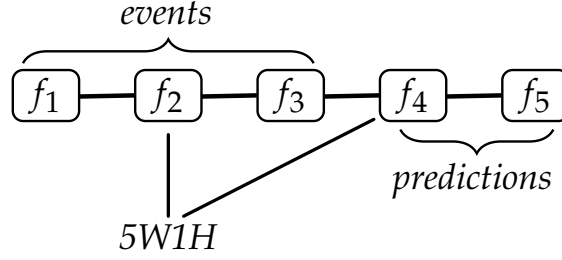


Figure K.1: The Anatomy of a Story

Each block f_i is a statement. A story – the entire chain of blocks $(f_i)_i$ – is a chronologically-ordered, finite list of statements. Each statement encodes information along six dimensions: who, what, where, when, why, how (5W1H). Realized facts are called “events”; future hypothesized facts are “predictions”.

K.2 Predictions, not Events, Drive Narrative Clustering

As illustrated in Figure K.1, each story’s facts can be classified into realized events and hypothesized predictions. In this first set of tests, I check which kinds of statements drive community membership. Are narratives defined primarily by a focus on the same subsets of the past? Or by positing similar predictions about the future?

Figure K.2 first establishes that there is no systematic statistical difference between stories’ event-similarities whether or not the stories are in the same narrative. Prediction similarity, conversely, is about 14% higher for stories in the same narrative than stories classified in different narratives.

I then check whether this difference translates into genuine explanatory power over narrative membership. That is, I estimate models of the form:

$$\mathbb{1}_{\text{narrative}(i)=\text{narrative}(j)} \sim z_{\text{type},ij} + X_{ij} \quad (34)$$

for story-pair (i, j) , where types are events or predictions, and type-specific narratives are obtained by running the narrative-clustering algorithm on the type-specific subset, treating it as the whole story. For robustness I repeat the analysis with both linear probability and logit models.

I test the degree to which event and prediction similarity contribute to narrative co-membership. To do so, following Lipovetsky and Conklin (2001) and Shorrocks (2013), I compute the Shapley (1953) value of each similarity-score towards explaining the overall variation (R^2 for linear probability models; log-likelihood for logit models).²⁸

²⁸To do so, I test model 34 on every subset of variables of interest. Here: $\{\emptyset, \{z_{\text{events},ij}\}, \{z_{\text{predictions},ij}\}, \{z_{\text{events},ij}, z_{\text{predictions},ij}\}\}$. Then, I apply the standard Shapley value formula, treating the R^2 (or log-likelihood) as the total value associated to a “coalition” (i.e., set of explanatory variables).

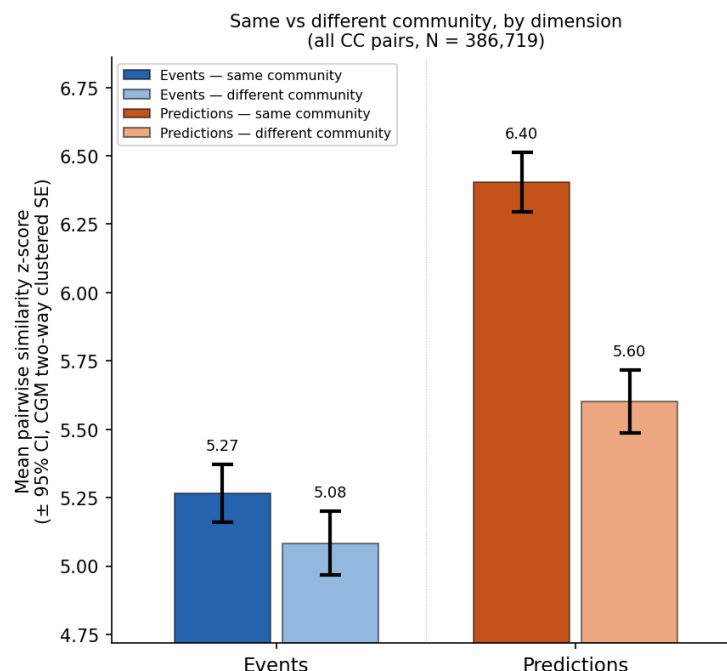


Figure K.2: Narrative-Community Membership and Similarity in Events and Predictions

Mean story-pair event and prediction similarity by narrative co-membership. Bars report mean standardized pairwise similarity z -scores in stories' events and predictions, separately for story pairs assigned to the same narrative community and for pairs in different communities. Sample: complete-case pairs with non-missing event and prediction similarity ($N = 386,719$). Error bars are 95% confidence intervals with [Cameron et al. \(2011\)](#) two-way clustered standard errors due to the dyadic structure of observations ([Aronow et al., 2015](#)).

Table K.1 presents the results. Across specifications, similarity in predictions has about 3 times the explanatory power of similarity in events, with relative Shapley shares of 72-80% against 20-26%, confirming the primacy of predictions in defining the boundaries of narrative-clustering. Results are robust to the inclusion of controls for stories coming from articles from the same geographic region, same newspaper, and days elapsed between publication dates. Interestingly, the R^2 for the model with a same-region control is higher than the one with the same-newspaper control, but both offer an increase in goodness of fit (by 17% of R^2 for same-region and by 6% for same-newspaper controls, relative to the specification with only a control for days-in-between-publications).

Not all stories have both events and predictions. The results in Table K.1 reflect the sample with both. In Appendix K.5 (Table K.5) I perform a robustness check in which I impute missing data. Because an absence of events or predictions is, most plausibly, not an issue of mismeasurement but a true indication of an underlying article which makes no claim about the future, the appropriate imputation strategy is to treat missing data as a zero. Results remain consistent.

<i>Panel A: Linear Probability Model</i>				
	(1)	(2)	(3)	(4)
z_{events}	21.1%	20.1%	25.6%	24.2%
$z_{\text{predictions}}$	78.9%	79.9%	74.4%	75.8%
Days between		✓	✓	✓
Same region			✓	
Same newspaper				✓
Overall R^2	0.0173	0.0392	0.0458	0.0416
N	386,653	386,653	212,866	212,870

<i>Panel B: Logit Model</i>				
	(1)	(2)	(3)	(4)
z_{events}	22.7%	22.0%	27.7%	26.7%
$z_{\text{predictions}}$	77.3%	78.0%	72.3%	73.3%
Days between		✓	✓	✓
Same region			✓	
Same newspaper				✓
Log-likelihood	-257492.69	-253175.82	-137966.73	-138365.79
N	386,653	386,653	212,866	212,870

Table K.1: Narrative-Community Membership as Explained by Events and Predictions: Shapley decompositions

This table reports Shapley decompositions of model explanatory power for whether two stories belong to the same narrative community. Panel A reports linear probability models, where explanatory power is measured by R^2 ; Panel B reports logit models, where explanatory power is measured by the model log-likelihood. z_{events} and $z_{\text{predictions}}$ are standardized similarities between the two stories' events and predictions, respectively. Entries in those rows are relative Shapley shares, that is, the percentage of explanatory power attributable to each predictor among the focal narrative-similarity variables. Columns differ by included controls, indicated by checkmarks: days between measures the number of days elapsed between the two underlying articles' publications; same region and same newspaper are dummies based on a classification of article sources. (NB: No p-values or significance stars are reported because Shapley shares are variance/log-likelihood decompositions rather than coefficient estimates.)

K.3 Story Micro-Structure (5W1H) as a Predictor of Event and Prediction Similarity

Each fact of each story admits a description through the six 5W1H structural dimensions: who, what, where, when, why, and how (cf Figure K.1). Thus, for each story, I also obtain a list a chain of who's, a list of what's, and so forth – where each element in the dimension-specific list is the corresponding fact's dimension. I run the entire alignment-scoring algorithm on these 5W1H- and event/prediction-specific lists, separately, – extracting dimension-specific standardized similarity scores – in order to study whether the (similarity in) emergent structural patterns at the sub-statement level explain patterns in similarity in stories' events and predictions.

I now estimate models of the form

$$z_{\text{type},ij} \sim \sum_d z_{d,ij} + \text{days_between_publications}_{ij} + X_{ij}$$

for z the standardized optimal-alignment similarity-scores, both for the type (event or prediction) and d the relevant 5W1H dimensions, and i, j the identifiers of two stories under consideration.²⁹ Like in the analysis of how event or prediction similarity are related to narrative-community membership, I compute the Shapley value for each of the 5W1H dimensions. The shares of total R^2 attributable to each dimension are summarized in Figure K.3.

As shown in Table K.2, similarity in events and predictions are driven by quite different subsets of the 5W1H dimensions. Event similarity is primarily associated to similarity in the *what* and *who* dimensions, at about 40 and 23% of the joint R^2 , which, itself, is quite high for this kind of structural decomposition: the R^2 ranges between 45 and 52%, depending on the inclusion of controls (days elapsed between the two articles' publication dates, whether the two articles originate from the same region or newspaper). The other 5W1H dimensions remain low, explaining about 10% of the R^2 .

Prediction similarity has a fundamentally different structural fingerprint. The *how* and *why* dimensions rise in prominence, explaining 28-30 and 17-20% of the R^2 , respectively. The *what* and *who* dimensions, while still meaningful are less important than they were for events, explaining jointly only 46% (instead of 63%) of the R^2 . The remaining

²⁹Retaining the full 5W1H dimension-story allows me to investigate whether the *entirety* of what a story says about, for instance, the *how*-dimension matters for the story's hypothesized predictions. This is structurally more sound and methodologically-agnostic. It is not obvious that one should want to restrict to within-prediction (or within-event) stated sub-fact dimensions as an explanatory variable for prediction (event) similarity: for instance, a natural conjecture could be that the earlier facts' *how*'s are actually the ones most salient for the hypothesized predictions as they fix the mechanism at hand. Moreover, the possibility of temporal overlap between some events and predictions across different stories is such that restrictions could truncate data in meaningful ways.

when, *where* dimensions are vanishingly small, suggesting that similarity in predictions may cut across time and space in a way that realized events do not. The R^2 itself is much lower as well: the 5W1H dimensions and controls explain between only 15 and 24% of total variation in prediction similarity.

In both cases, results are very stable across control specifications, which rules out temporal clustering, geographic proximity or same-outlet confounds as the driving force behind structural patterns. Here, too, there is a missing data concern to be addressed. Unlike missing events or predictions, however, a missing 5W1H dimension is less about intentional omission and more of a measurement error. The intuition here is that not every story must have a prediction (e.g., purely backwards-looking news articles with no claims about the future are common), but an omniscient narrator (or analyst, or observer) could infer and fill in a missing motivation (*why*) or mise-en-scène (*where*) – but ought not to invent a separate prediction altogether. As such, for robustness, I repeat the above exercise with data imputed by dimension-specific mean values (see Table K.6). Results are robust to data imputation: *what* and *who* remain the dominant dimensions of event-similarity; and the Shapley values of the *how* and *why* increase, positioning them as uncontested explanatory variables of prediction-similarity.³⁰

These results, taken together, suggest a natural dichotomy between events, driven by *plot* (what, who), and predictions, reliant on *mechanism* (how, why), and confirms that the two objects are meaningfully structurally different.

K.4 Story-structure and Piecewise-Constant Narrative Regimes

The piecewise-constant regimes reflect not only the existence of news shocks per se, but also of the degree to which these are, in fact new and shocking to market participants – that is, how much they correspond to shifts in agents’ beliefs about tariffs’ aggregate price impacts (as measured by tariff-attributable commodity price changes). It is, therefore, natural to have the intuition that narrative internal coherence and informativeness should be related. As economic intuition would suggest that a narrative’s predictions would drive its pricing implications and because section K.2 established that narratives clustered on future-oriented predictions, it makes sense that “internal coherence” should bear specifically on the coherence of predictions. I hypothesize that the relationship between the similarity of predictions made within a narrative on a given day and the informativeness of that narrative should be negatively related. This suggests an interpretation of absence of consensus as revelatory of learning potential. While the narrative entertains some non-

³⁰Though in the complete-case sample predictions are still reliant on the who-what dimensions, this dependence vanishes altogether with data imputation. Only the why-how dimensions are robust for prediction structure, and indeed appreciate in importance with data imputation.

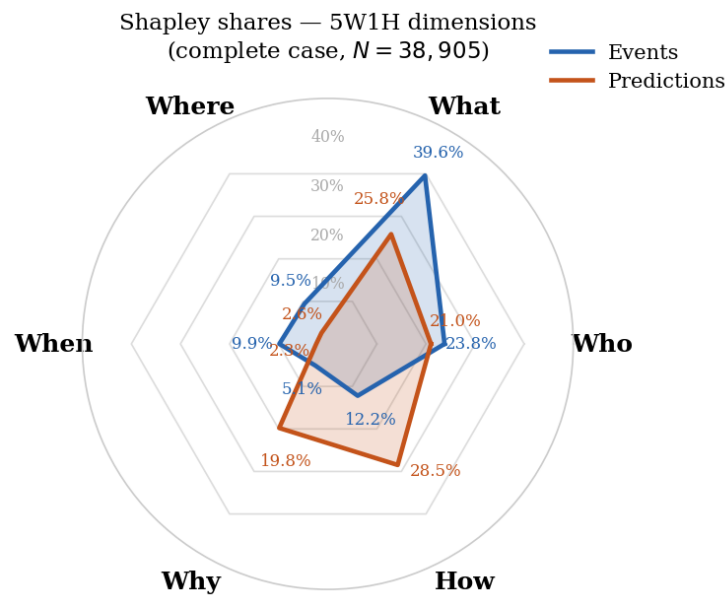


Figure K.3: Event and Prediction Similarity as Explained by the 5W1H dimensions: Shapley decompositions

This figure reports relative Shapley shares from the 5W1H similarity models (Column 1). The solid blue line shows the decomposition for event similarity; the dashed orange line shows the decomposition for prediction similarity. Each axis corresponds to one 5W1H dimension, and values indicate the percentage of explanatory power attributable to that dimension among the six focal predictors.

<i>Panel A: Event Similarity</i>				
	(1)	(2)	(3)	(4)
<i>Who</i>	23.8%	23.3%	23.1%	23.1%
<i>What</i>	39.6%	40.5%	39.5%	41.1%
<i>Where</i>	9.5%	9.1%	8.5%	8.5%
<i>When</i>	9.9%	9.8%	9.9%	10.5%
<i>Why</i>	5.1%	5.1%	6.3%	5.0%
<i>How</i>	12.2%	12.1%	12.7%	11.8%
Days between		✓	✓	✓
Region fixed effects			✓	
Same newspaper				✓
Overall R^2	0.4466	0.4539	0.5228	0.5180
<i>N</i>	38,905	38,905	21,884	21,884

<i>Panel B: Prediction Similarity</i>				
	(1)	(2)	(3)	(4)
<i>Who</i>	21.0%	22.2%	20.8%	21.5%
<i>What</i>	25.8%	25.2%	26.6%	26.1%
<i>Where</i>	2.6%	3.0%	3.6%	3.8%
<i>When</i>	2.3%	2.1%	2.3%	2.0%
<i>Why</i>	19.8%	18.1%	19.2%	16.6%
<i>How</i>	28.5%	29.5%	27.5%	30.0%
Days between		✓	✓	✓
Region fixed effects			✓	
Same newspaper				✓
Overall R^2	0.1460	0.1481	0.2076	0.2364
<i>N</i>	38,905	38,905	21,884	21,884

Table K.2: Event and Prediction Similarity as Explained by the 5W1H dimensions: Shapley decompositions

This table reports Shapley decompositions of model explanatory power for event and prediction similarity. Panel A uses standardized event similarity scores as the dependent variable; Panel B uses prediction similarity as the dependent variable. The predictors of interest are the standardized similarity scores between the two stories along the 5W1H dimensions: who, what, where, when, why, and how. Entries in the 5W1H rows are relative Shapley shares, i.e. the percentage of explanatory power attributable to each dimension among the focal predictors. Columns differ by included controls, indicated by checkmarks: the number of days elapsed between the publication of two articles, and whether they originate from the same geographic region or newspaper. No p-values or significance stars are reported because Shapley shares are R^2 decompositions rather than coefficient estimates.

trivial variability in predictions, it is still being priced in and is informative. Once it has been priced, nothing more can be learned – or debated – and so the narrative is reduced to banal consensus.

Measurement of within-narrative coherence and intensity of narrative regime Within each of the fourteen tariff narratives,³¹ I define *cohesion* as the (standardized) mean pairwise similarity of articles’ predictions over a backward-looking rolling seven-day window. For narrative informativeness, I take the absolute value of the narrative’s per-article regime (Fused LASSO time-varying coefficient).

Empirical Evidence and Interpretation Figure K.4 and Table K.4 present the results. Sorting the fourteen narratives each day by cohesion, the least cohesive quintile has a mean absolute coefficient of about 3.4 basis points (bps) per article and the most cohesive quintile about 2.3 bps per article, a gap of approximately 40 percent of the mean (Figure K.4; left panel). The average of these daily cross-sectional slopes is negative and significant ($t = -2.53$) (Figure K.4; left panel). I then test the relationship by fitting a quadratic

$$\underbrace{\left| \overbrace{\beta_{kt}}^{\text{per-article narrative regime}} \right|}_{\text{narrative informativeness}} \sim \text{cohesion} + \text{cohesion}^2$$

with day fixed effects Table K.4. I find the relationship to be downward-sloping, statistically significant. It is even convex, but the minimum lies so far in the right tail – above an average cohesion score of 14 – that 97 percent of observations sit on the declining portion of the curve. This should, therefore, be taken as evidence of diminishing marginal returns, not of a true reversal in the trend. Moving from the 5th to the 95th percentile of cohesion lowers the fitted absolute coefficient by 1.6 basis points per article.

Narrative informativeness is highest when within-narrative predictions tolerate variation, and lower through the rest of the distribution. This is consistent with a broadly Popperian view: a narrative can be informative only if something can be learned; and learning means ruling out falsifiable predictions. A narrative which ceases to generate non-trivial variability in predictions is no longer informative (most likely because all of its substantive predictions have already been corroborated or refuted, and hence the narrative is fully priced in).

Robustness Binned means and cubic splines reproduce the same pattern. The decline is still present when cohesion is lagged seven trading days (so the similarity window and

³¹I exclude the catch-all “other” category.

the return date do not overlap), and it remains after controlling for the log number of articles in the window (Table K.3).³²

K.5 Narrative Structure: Shapley values under data imputation

Here I present the results of the data imputation exercises of section K.4 of the paper. Table K.5 presents the results for zero imputation for missing observations in events-vs-predictions tests, and Table K.6 presents the results for mean imputation for 5W1H tests.

³²Heavier coverage itself comes with a smaller per-article coefficient, as would be expected if many similar articles share one narrative loading, but coverage and cohesion are only weakly correlated.

Panel A: $ \beta_{k,t} \sim \bar{s}_{k,t} + \bar{s}_{k,t}^2$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\bar{s}_{k,t}$	-0.000042** (0.000018)	-0.000034** (0.000016)	-0.000045** (0.000020)	-0.000042** (0.000019)	-0.000021 (0.000015)	-0.000020 (0.000015)	-0.000021 (0.000017)	-0.000023 (0.000017)
$\bar{s}_{k,t}^2$	0.000001** (0.000001)	0.000001* (0.000001)	0.000002** (0.000001)	0.000001* (0.000001)	0.000001* (0.000001)	0.000001* (0.000001)	0.000001* (0.000001)	0.000001* (0.000001)
$\ln(\text{articles}_{k,t} + 1)$		-0.000131*** (0.000021)		-0.000164*** (0.000019)		-0.000018 (0.000015)		-0.000023 (0.000019)
Narrative FE					✓	✓	✓	✓
Day FE			✓	✓			✓	✓
N	1,048	1,048	1,048	1,048	1,048	1,048	1,048	1,048
R^2 (within)	0.018	0.123	0.020	0.152	0.012	0.016	0.012	0.017
R^2 (overall)	0.018	0.123	0.044	0.173	0.642	0.644	0.656	0.658

Panel B: $ \beta_{k,t} \sim \bar{s}_{k,t-7} + \bar{s}_{k,t-7}^2$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\bar{s}_{k,t-7}$	-0.000035*** (0.000012)	-0.000030*** (0.000011)	-0.000039*** (0.000014)	-0.000040*** (0.000012)	-0.000011 (0.000007)	-0.000011 (0.000007)	-0.000010 (0.000008)	-0.000009 (0.000008)
$\bar{s}_{k,t-7}^2$	0.000001*** (0.000000)	0.000001* (0.000000)	0.000001*** (0.000000)	0.000001** (0.000000)	0.000001** (0.000000)	0.000001** (0.000000)	0.000001** (0.000000)	0.000001** (0.000000)
$\ln(\text{articles}_{k,t-7} + 1)$		-0.000119*** (0.000018)		-0.000151*** (0.000017)		-0.000000 (0.000014)		0.000011 (0.000018)
Narrative FE					✓	✓	✓	✓
Day FE			✓	✓			✓	✓
N	950	950	950	950	950	950	950	950
R^2 (within)	0.013	0.097	0.014	0.122	0.006	0.006	0.006	0.007
R^2 (overall)	0.013	0.097	0.040	0.145	0.634	0.634	0.649	0.649

Table K.3: Cohesion and Informativeness: Fixed Effects and Coverage

The dependent variable is informativeness, $|\beta_{k,t}|$: the absolute per-article narrative regime (the association of one additional article in narrative k with the daily return of the commodity long-short portfolio). Cohesion $\bar{s}_{k,t}$ is the mean pairwise standardized similarity of predictions among articles in narrative k published in the seven calendar days ending on date t . The sample is the fourteen tariff narratives from 1 April to 31 July 2025, with the catch-all “other” category excluded: 1,048 narrative-days in Panel A. Panel B lags cohesion by seven trading days, so the similarity window ends before the return date, and has 950 observations. A coefficient of -0.000045 is -0.45 basis points of return per article for a one-point difference in cohesion. Columns (1) and (2) include no fixed effects. Columns (3) and (4) include day fixed effects. Columns (5) and (6) include narrative fixed effects. Columns (7) and (8) include both. Even-numbered columns add $\ln(\text{articles} + 1)$, the log number of articles in the same seven-day window. Standard errors in parentheses are Driscoll-Kraay with a Bartlett kernel, which allows serial correlation of $|\beta_{k,t}|$ within a narrative and correlation across narratives on the same day. The within R^2 computes the R^2 exclusive of what is explained by fixed effects; the overall R^2 includes them. Columns (1) and (3) of each panel are the four columns of Table K.4. Column (3) of Panel A is the quadratic drawn in the right panel of Figure K.4.

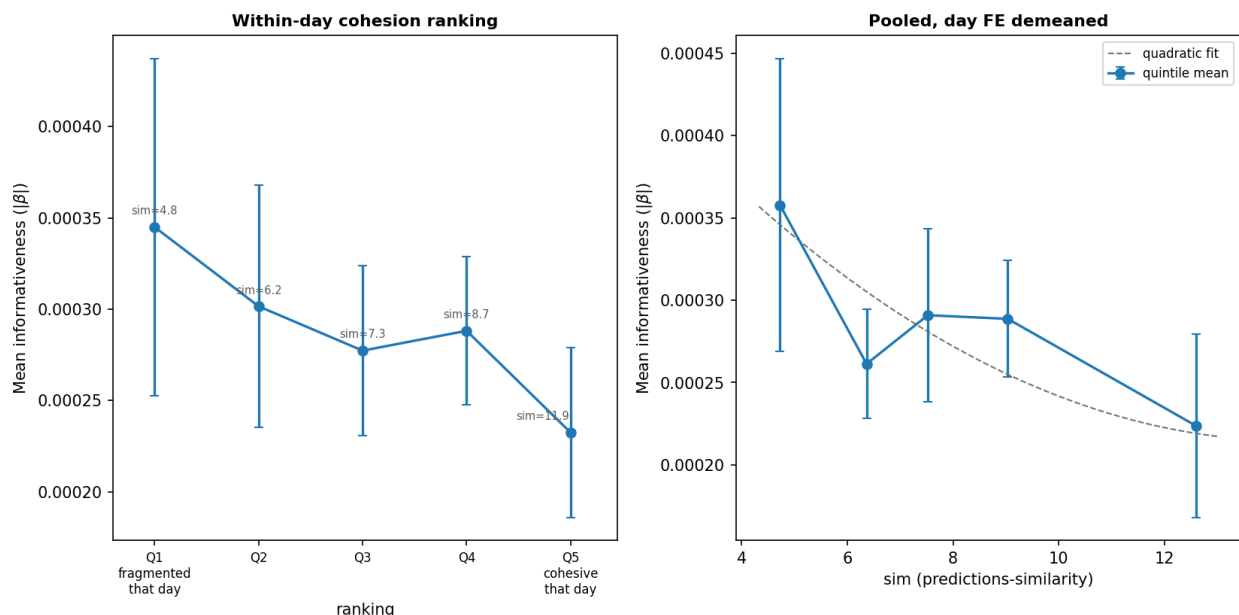


Figure K.4: Within-Narrative Cohesion and Informativeness

This figure examines the relationship between within-narrative cohesion and informativeness. Cohesion is the mean pairwise standardized similarity of articles' predictions over a trailing seven-day window. Informativeness is the mean absolute per-article narrative regime (the association of an additional article with the daily return of the commodity long-short portfolio, across the fourteen tariff narratives from 1 April to 31 July 2025). The left panel asks whether, on a given day, the narratives that are more cohesive (relative to other narratives that day) have lower informativeness. Narratives are sorted, each day, into quintiles of that day's cohesion, from the most fragmented narrative that day (Q1) to the most cohesive (Q5). Labels give the average similarity in the quintile. The right panel asks whether informativeness overall falls as cohesion increases, and checks the whether the data ever recovers a meaningful upward-sloping portion of the curve. The absolute coefficient is residualized on day dummies and re-centered at its sample mean – so that effects are not driven by overall informative or uninformative days – then averaged within quintiles of the similarity level pooled across days (cf Column (2) of Table K.4). The dashed line is a quadratic fit to the underlying narrative-day observations and declines over the range of quintile means shown. About 97% of observations lie on the decreasing portion of the quadratic fit. Throughout, vertical bars are 95% DriscollKraay confidence intervals. In essence, the first panel ensures the effect effect is not driven by more or less cohesive days; while the second panel ensures the effect is not a function of more or less informative days. The two panels look very similar because only about 8.7% of the variation in cohesion is a shift in the daily average; the other 91.3% is differences across narratives on the same day. About 71.4% of days already spread the fourteen narratives across all five absolute bins. As a result, 60.7% of narrative-days land in the same quintile under both rules, and 36.3% land in a neighboring quintile.

	Informativeness ($ \beta_{kt} $)			
	Contemporaneous cohesion		Lagged cohesion	
	(1)	(2)	(3)	(4)
Cohesion	-0.000042** (0.000018)	-0.000045** (0.000020)	-0.000035*** (0.000012)	-0.000039*** (0.000014)
Cohesion ²	0.000001** (0.000001)	0.000002** (0.000001)	0.000001*** (0.000000)	0.000001*** (0.000000)
Day FE		✓		✓
N	1,048	1,048	950	950
R ² (within)	0.018	0.020	0.013	0.014
R ² (overall)	0.018	0.044	0.013	0.040

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table K.4: Within-Narrative Cohesion and Informativeness

The dependent variable is informativeness: the mean absolute per-article narrative regime (the association of an additional article with the daily return of the commodity long-short portfolio, across the fourteen tariff narratives from 1 April to 31 July 2025). The independent variable is cohesion – the mean pairwise standardized similarity of articles’ predictions over a trailing seven-day window – and its quadratic term. Columns (1) and (2) use contemporaneous cohesion. Columns (3) and (4) lag cohesion by seven trading days, so the similarity window does not include the return date. Columns (2) and (4) include day fixed effects. Standard errors in parentheses are DriscollKraay. The within R^2 computed after the fixed effects are removed; the overall R^2 includes them. The sample is the fourteen tariff narratives from 1 April to 31 July 2025 (with the catch-all “other” category excluded). Column (2) is the regression which informs the right panel of Figure K.4 specification: the points are quintile means of this regression, and the dashed curve is its quadratic fit.

<i>Panel A: Linear Probability Model</i>				
	(1)	(2)	(3)	(4)
z_{events}	31.2%	30.7%	28.8%	28.3%
$z_{\text{predictions}}$	68.8%	69.3%	71.2%	71.7%
Days between		✓	✓	✓
Same region			✓	
Same newspaper				✓
Overall R^2	0.0356	0.0559	0.0605	0.0586
N	906,159	906,159	490,658	490,662
<i>Panel B: Logit Model</i>				
	(1)	(2)	(3)	(4)
z_{events}	32.6%	32.3%	30.9%	30.6%
$z_{\text{predictions}}$	67.4%	67.7%	69.1%	69.4%
Days between		✓	✓	✓
Same region			✓	
Same newspaper				✓
Log-likelihood	-609461.23	-599684.36	-323584.82	-323948.77
N	906,159	906,159	490,658	490,662

Table K.5: Shapley values of events-vs-predictions: missing imputed as zero

<i>Panel A: Event Similarity</i>				
	(1)	(2)	(3)	(4)
<i>Who</i>	26.3%	25.9%	24.5%	25.0%
<i>What</i>	49.4%	49.9%	50.0%	49.6%
<i>Where</i>	6.9%	6.7%	5.5%	5.6%
<i>When</i>	6.6%	6.7%	7.3%	7.6%
<i>Why</i>	2.8%	2.8%	3.3%	3.2%
<i>How</i>	8.0%	8.0%	9.3%	9.1%
Days between		✓	✓	✓
Region fixed effects			✓	
Same newspaper				✓
Overall R^2	0.2676	0.2704	0.3093	0.3002
<i>N</i>	299,440	299,440	167,166	167,170

<i>Panel B: Prediction Similarity</i>				
	(1)	(2)	(3)	(4)
<i>Who</i>	1.4%	1.5%	4.9%	3.1%
<i>What</i>	3.5%	4.2%	5.3%	3.8%
<i>Where</i>	1.9%	1.8%	0.5%	0.3%
<i>When</i>	0.3%	0.2%	0.6%	0.4%
<i>Why</i>	33.0%	30.3%	34.4%	34.3%
<i>How</i>	59.9%	62.0%	54.3%	58.2%
Days between		✓	✓	✓
Region fixed effects			✓	
Same newspaper				✓
Overall R^2	0.0128	0.0146	0.0375	0.0442
<i>N</i>	299,440	299,440	167,166	167,170

Table K.6: Shapley values of 5W1H: missing imputed as means

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