Text-Based Analyses of Stock Markets, Business Performance, and Policy Uncertainty

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Lecture Plan

1. "What Triggers Stock Market Jumps?," Scott Baker, Nick Bloom, Steven J. Davis and Marco Sammon, April 2025.
   - A low-tech, human-intensive text-based analysis.
2. "Macro Shocks and Firm-Level Response Heterogeneity," Steven J. Davis, Stephen Hansen, Cristhian Seminario-Amez, May 2025.
   - A text-intensive, machine-learning approach
3. Observations on the U.S. Trade Policy Rupture.
   - Drawing on several text-based and other analyses
   - See "Destructive Trade Policy" for remarks that cover some of the same ground.

What Triggers Stock Market Jumps?

Baker, Bloom, Davis and Sammon

Distilling Information and Perceptions about the Forces that Drive Big Stock Market Jumps

- Benchmark view: stock price changes reflect rational responses to news about discount rates and cashflows.
    - → large daily moves should be accompanied by readily identifiable developments that affect discount rates and anticipated profitability.
    - Contemporaneous news accounts contain information about the proximate drivers of these moves.
- Stock price behavior may not conform to the benchmark view.
    - Even when speculative or irrational forces are in play, we expect news accounts to discuss the perceived drivers of market moves.

Thus, we turn to newspapers to distill information about what triggers big (daily) jumps in national stock markets.

What We Do

1. Characterize contemporaneous perceptions of large daily jumps in 19 national stock markets.
   - Develop and implement a taxonomy of jump drivers.
   - Identify proximate jump cause, clarity as to cause, and geographic source of the market-moving news.
2. How: Train, deploy, and oversee >45 human readers who read and code next-day newspaper articles.
   - Coding Guide (142 slides) – for training and reference.
3. Study jump features: drivers, clarity, geography, relation to monetary and fiscal policy, relation to volatility,…

How We Code Daily Stock Market Jumps

1. Set daily jump threshold at |2.5%| return for U.S.
   – Picks up 3.5% of trading days from 1900 to 2023 (≈1,200 US jumps)
   – Jumps: 20% of total daily return variation, half of squared variation
2. Locate pertinent next-day newspaper articles (same evening in internet era)
   – WSJ, NYT, Washington Post, LA Times, Chicago Tribune, Financial Times
   – Jumps >|2.5%| almost always attract coverage in next-day U.S. newspapers
   – Deploy multiple readers per jump and newspaper.
   – Randomize jump and paper assignments to readers and across time, cross validate, …
3. Record:
   – Category of primary jump reason (secondary reason, too, when stated)
   – Key article passage(s) and coder's paraphrase of journalist's explanation
   – Journalist confidence about what triggered the jump (three-point scale)
   – Coder's ease of discerning and classifying the primary jump reason (three-point scale)
   – Geographic origin(s) of jump-triggering news

Notable Aspects of Our Measurement Efforts

- **Scale:** 8,019 stock market jumps + 455 bond market jumps
- **Scope:** 19 national markets and 90+ years for the US and UK
- **Granularity:** Detailing jump reasons and geographic origin of market-moving news
- **Novel quantification:** Perceived clarity of jump reason
- **Policy**: Uncovering distinctive aspects of policy-triggered jumps
- **Volatility dynamics**: Relationship of jump reason and jump clarity to market volatility and dispersion of firm-level returns.

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Preview of Main Findings

1. Jumps have become more grounded in readily perceived news developments over the past century.
2. News about monetary policy and government spending accounts for a highly disproportionate share of upward jumps.
3. Upward jumps attributed to monetary policy and government spending shocks are much more likely after a stock market crash.
   - "Fed put" emerged decades before the 1990s, characterizes fiscal policy as well, and extends to other countries.
4. Jumps triggered by monetary policy foreshadow much lower volatility than other jumps (and lower absolute volatility)
5. Leading newspapers attribute 38 percent of jumps in their own national stock markets to US economic and policy developments.
   - US role in this regard dwarfs that of Europe and China.

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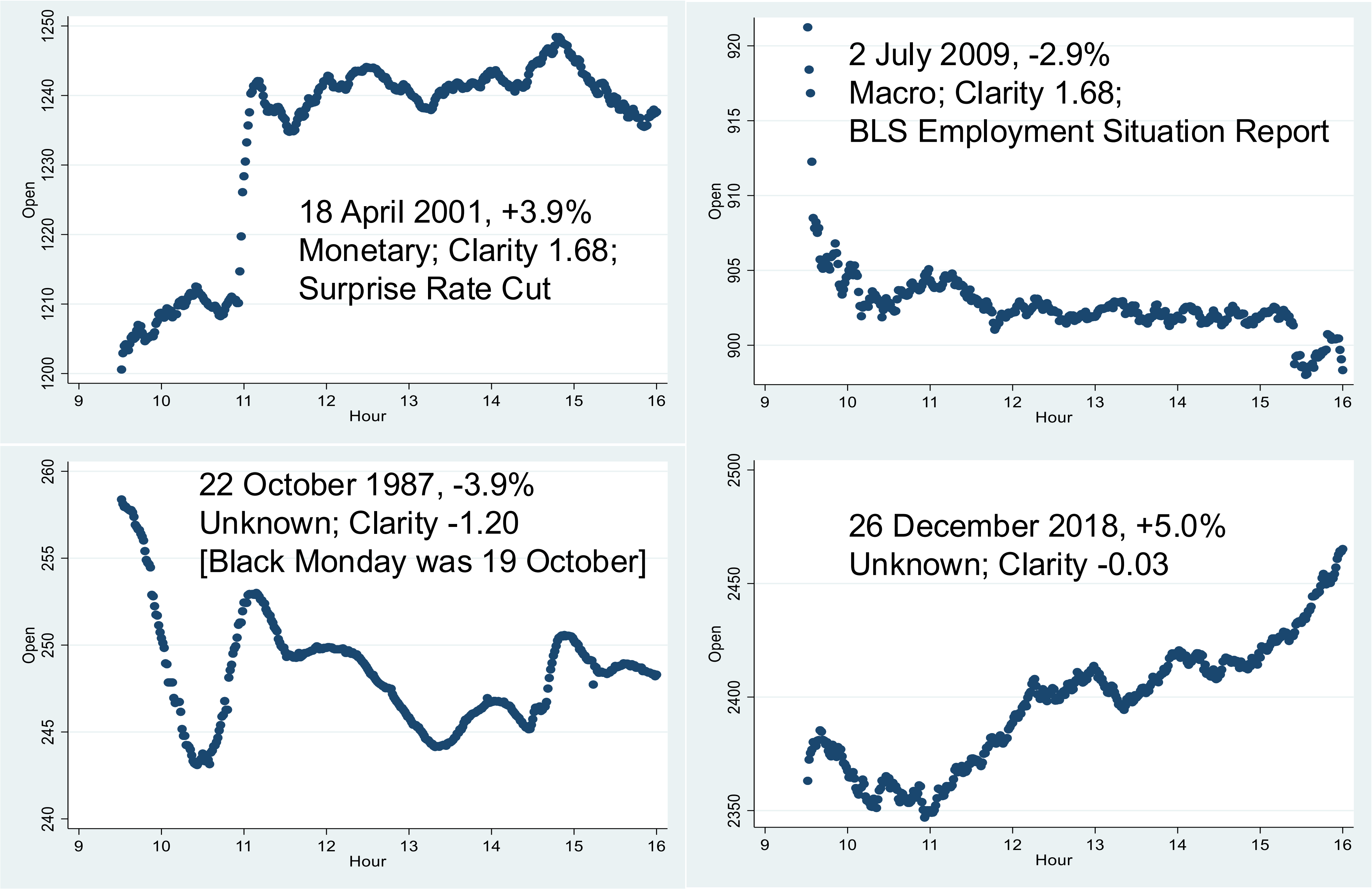
Jump Categories

Policy Categories	Non-Policy Categories
Government Spending	Macroeconomic News & Outlook
Taxes	Corporate Earnings & Outlook
Monetary Policy & Central Banking	Commodities
Exchange Rate Policy & Capital Controls	Foreign Stock Markets
International Trade Policy	Unknown & No Explanation
Sovereign Military & Security Actions	Terrorist Attacks
Regulation	Other Non-Policy
Elections & Political Transitions	No Article Found
Other Policy	

Our Coding Guide carefully defines each category and provides many examples of how to implement our classification scheme.

Figure 1: Intra-Day Moves Often, But Not Always, Point to the Likely Jump Reason



Notes: Each panel plots the S&P 500 index at 1-minute intervals from market open to close on the indicated date. We also report the percent change from the previous-day close to the current-day close, the primary jump reason (as classified by our human readers), and our measure of clarity as to jump reason. The clarity measure is standardized to mean zero and unit standard deviation. The top two panels also report the specific event that, according to newspaper accounts, triggered the jump.

Figure 2: Two Examples of Newspaper Articles about High-Clarity Jumps

Stock Prices Soar, as Investors Embrace a Surprise Rate Cut

By E.S. BrowningStaff Reporter of The Wall Street Journal
Updated April 19, 2001 4:22 am ET

SAVE PRINT TEXT

Another surprise interest-rate cut by the Federal Reserve sparked another strong rally in the stock market, with the Nasdaq Composite Index surging 8.1% and the Dow Jones Industrial Average rising nearly 4%.

The question for many investors: Is this rally for real, in contrast with several other short-lived run-ups since stocks began their bear-market drop last year?

The answer, traders and investors say, may depend on whether investors are more fearful of missing out if the market keeps going up, or more worried that the economic outlook will remain cloudy.

Bulls have been encouraged to see stock prices "reacting extremely well compared to the earnings numbers we are seeing," said Tim Heekin, director of trading at San Francisco investment bank Thomas Weisel Partners. Skeptics, however, say they are stunned by the idea that investors would jump back into tech stocks, in particular, after their collapse of the past year.

For the WSJ article at left, we classify the primary jump reason under **Monetary Policy & Central Banking (Policy),** because the article links the rise to the Fed's surprise interest rate cut. Geographic source is the **United States,** because the Fed is a U.S. policy-making institution. Journalist confidence is **High**, as the article explicitly links the move to the rate cut. Ease of coding is **Easy**.

Dow Drops 223.32 and Oil Slides --- Many Investors Sell Stocks, and Flock to Treasurys, After Soft Jobs Report

Lobb, Annelena; McKay, Peter A. **Wall Street Journal, Eastern edition; New York, N.Y.** [New York, N.Y]03 July 2009: C.1.

THE WALL STREET JOURNAL.

Full text Abstract/Details

An unexpectedly gloomy jobs report heightened anxiety that the economy mightn't be recovering as well as expected, prompting investors to sell stocks and commodities and flee to haven investments.

The Dow Jones Industrial Average slid 2.6%, the biggest decline ahead of a July 4 holiday in at least 50 years. The Dow closed at 8280.74, down 223.32 points, its lowest close since May 22 and the third consecutive week of declines. The New York Stock Exchange extended trading for 15 minutes at the end of the day because of a computer glitch.

Investors also abandoned commodities, reflecting the diminished optimism for economic growth and demand for raw materials. Crude slumped $2.58, or 3.7%, to $66.73 a barrel.

Instead, investors sought the relative safety of U.S. Treasurys and the U.S. dollar. The benchmark 10-year Treasury added 14/32 to 96 30/32, pushing down the yield to 3.494%. The dollar gained 1% against the euro and changed hands at 1.40 per euro late Thursday.

The 467,000 jobs lost in June surprised investors and fueled worries about the strength of the economy. After soaring from a low reached on March 9, stocks had plateaued. The jobs report came on the eve of earnings season, which begins next week with the report of Alcoa. Analysts have begun to worry that, even with the recent decline, stock investors may be overly optimistic about a second-half recovery.

For the WSJ article at right, we code the primary jump reason as **Macro News and Outlook (Non-Policy),** because the drop is clearly linked to the poor jobs report. Geographic source is the **US**. Journalist confidence is high, and ease of coding is **Easy.**

Figure 3: Two Examples of Articles (from Different Papers) about a Low-Clarity Jump

For the WSJ article below, we code the jump reason as **Unknown,** because "traders and investors were left scratching their heads."

U.S. MARKETS

Dow Industrials Leap More Than 1,000 Points

Rebound pulls Dow industrials, S&P 500 from brink of bear market

By Jessica Menton

Updated Dec. 26, 2018 11:07 p.m. ET

The Dow Jones Industrial Average surged more than 1,000 points for the first time in a single session Wednesday, rebounding after a bruising four-day selloff put the blue-chip index and the S&P 500 on the brink of a bear market.

All 30 stocks in the Dow industrials notched gains, as did each of the 11 sectors in the broader S&P. Shares of Amazon.com , Facebook and Netflix climbed more than 8%, while retailers including Kohl's and Macy's rallied as early data on the crucial holiday shopping season appeared robust. Energy stocks including Exxon Mobil and Chevron , meanwhile, rose alongside a nearly 9% climb in oil prices.

But as in many of the volatile days that have characterized markets since the end of September, investors and traders were left scratching their heads to explain the wild swing, with the Dow adding nearly 450 points in the last hour of the session.

The New York Times

Stocks Bounce Back From Edge of Bear Market

By Emily Flitter

Dec. 26, 2018

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Throughout Wall Street's December meltdown, analysts have been saying that markets were plunging despite plenty of evidence that the United States economy remains strong and corporate profit growth is healthy.

That argument finally found listeners on Wednesday, when early reports of a strong holiday-shopping season helped lift the S&P 500 by nearly 5 percent, its best day since 2009. The Nasdaq added 5.8 percent, and the Dow Jones industrial average rose just under 5 percent. That jump, over 1,086 points, represented the Dow's best single-session gain ever, although a number of days have eclipsed that in percentage terms.

A substantial rise in crude oil prices added to the lighter mood, as did efforts from the White House to ease up on criticism of the Federal Reserve.

For the NY Times article at right, we code the primary jump reason as **Macro News and Outlook,** because the article attributes the jump mainly to good news about consumer spending. Geographic source is the **US**. Journalist confidence and ease of coding are both **Medium.**

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Some Basic Patterns

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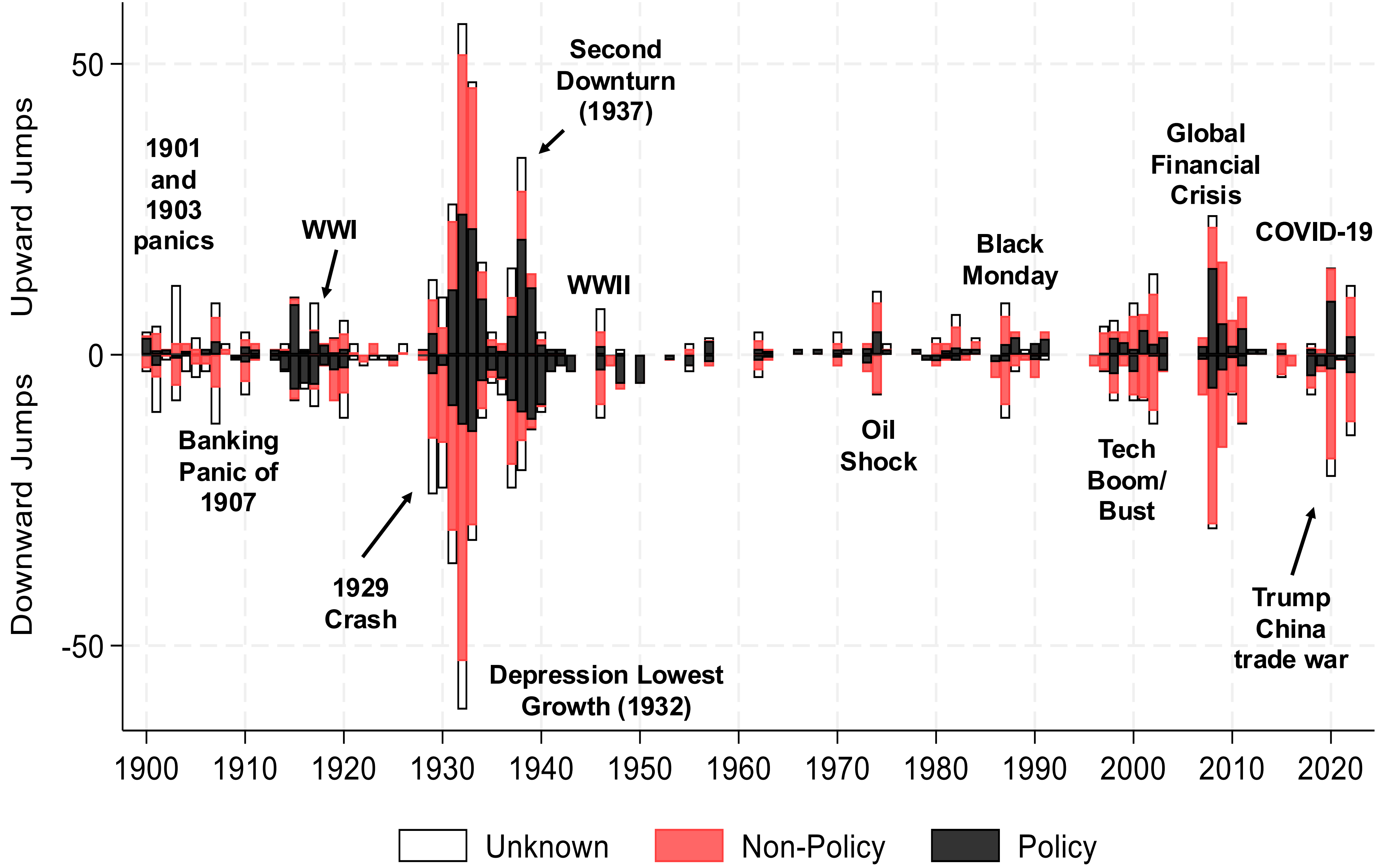
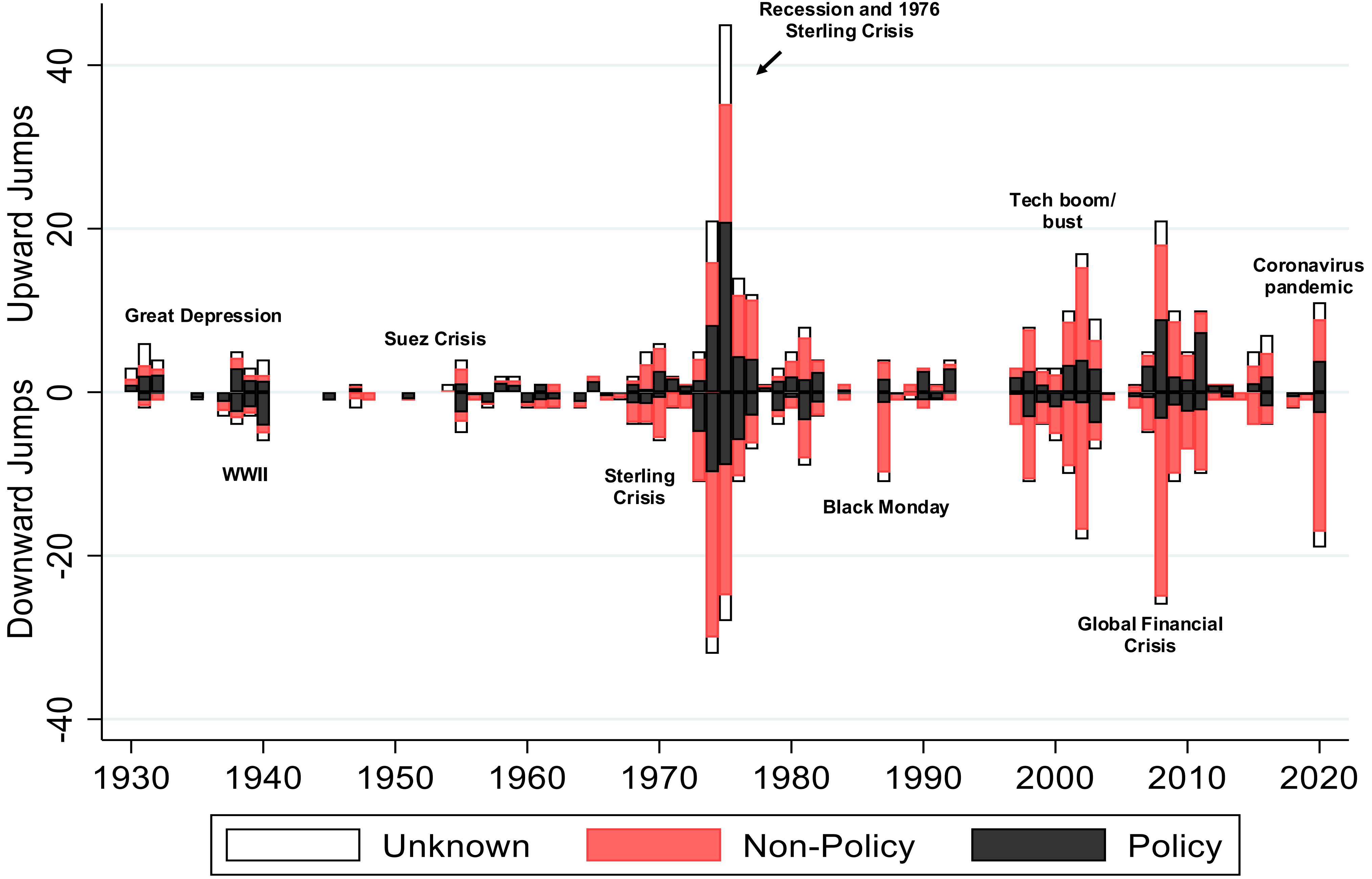
Figure 4: U.S. Jumps Per Year Vary Greatly but the Policy Share Is Fairly Stable, 1900-2023



Notes: Each bar is the number of positive or negative jumps in that year. Black and red shadings indicate jumps triggered by "Policy" and "Non-Policy" developments, respectively. The unshaded parts of each bar reflect jumps coded as "Unknown or "No Explanation Offered" plus five instances before 1926 of "No Article Found." There are no US jumps in 2023.

Figure A2: U.K. Jumps by Year, 1930-2020

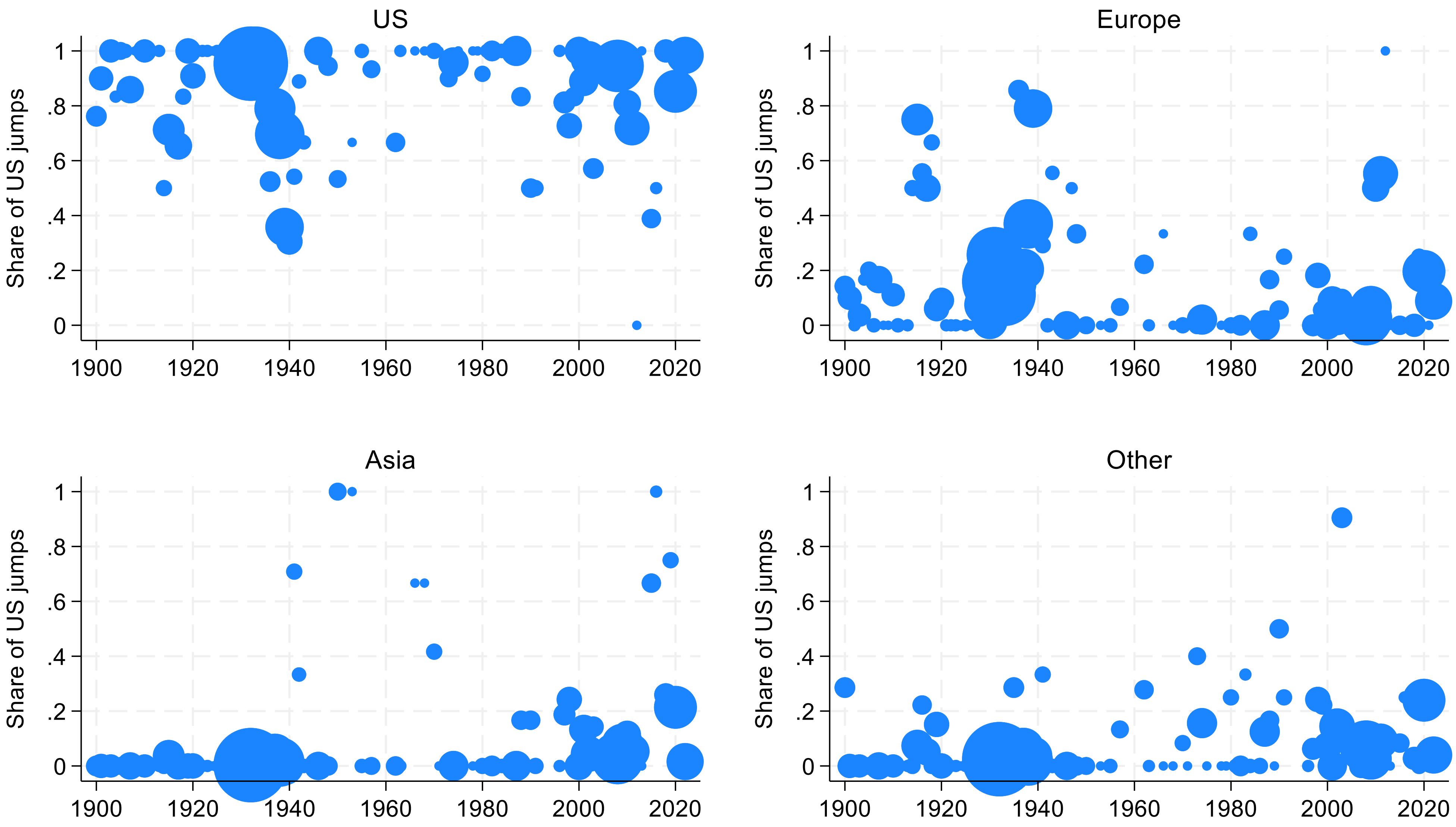


Notes: Each bar is the number of positive or negative jumps in that year. Shadings indicate the number of jumps triggered by "Policy", "Non-Policy" and "Unknown" news. Unknown includes "no article found". Data from 1930-2020.

Table 1. Distribution of Daily Jumps by Reason

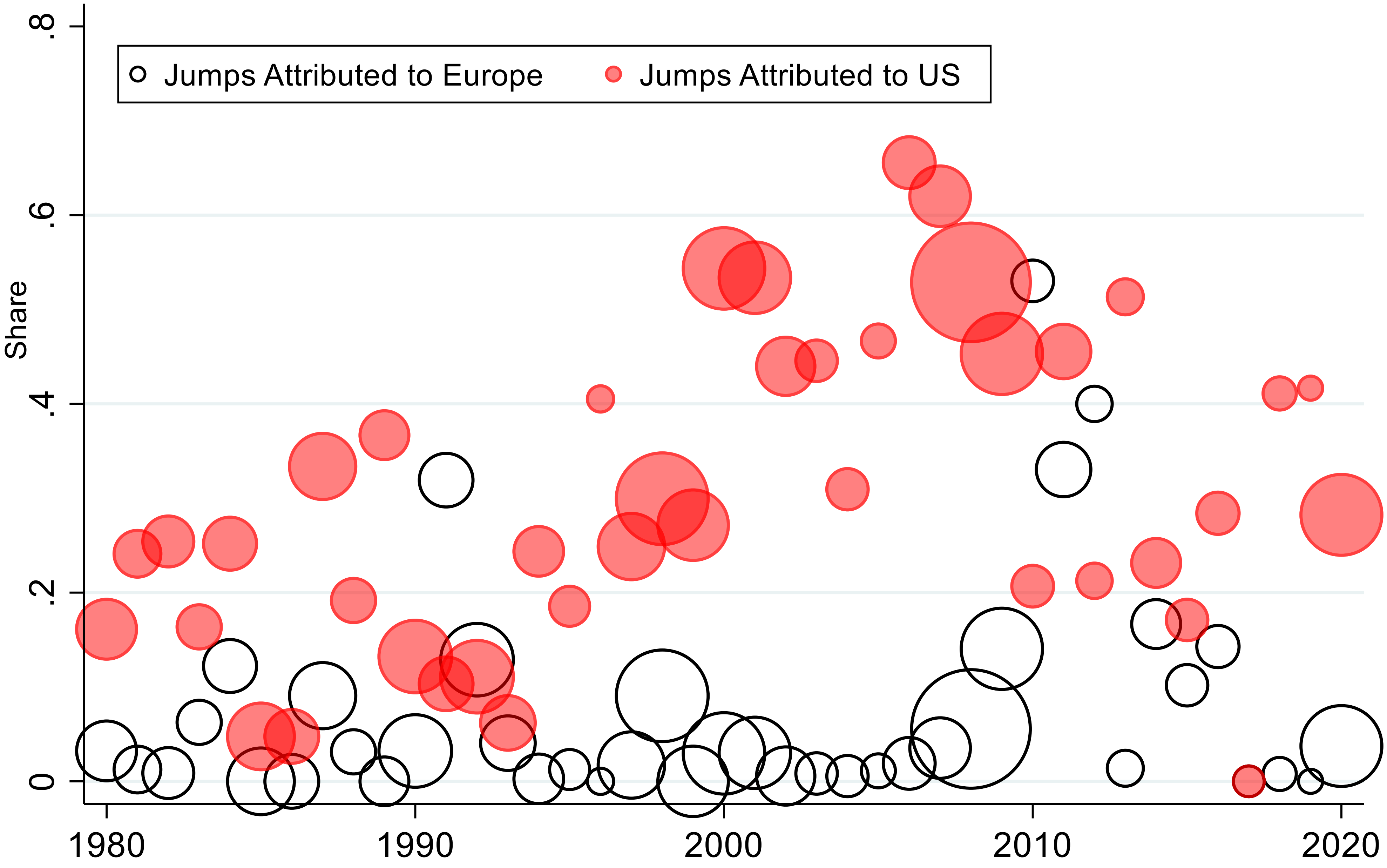
	US Equities		UK Equities	ROTW Equities	US Bonds
Time Period:	1900-2023	1980-2023	1930-2020	1980-2020	1970-2020
Macroeconomic News & Outlook	23.58	34.73	26.31	27.15	55.30
Corporate Earnings & Outlook	11.21	14.48	13.08	9.33	1.04
Sovereign Military & Security Actions	9.28	3.02	4.81	2.90	0.89
Monetary Policy & Central Banking	7.65	11.88	9.98	7.90	18.13
Government Spending	6.53	7.68	7.42	6.59	4.11
Commodities	5.53	1.82	2.42	2.39	1.18
Regulation	4.11	0.88	5.44	2.13	0.16
Other Non-Policy	4.20	6.20	3.84	3.44	2.50
Elections & Political Transitions	2.36	1.53	2.73	3.43	0.72
Other Policy	2.65	1.99	3.30	2.46	0.87
Taxes	1.68	1.02	1.12	0.65	1.18
Exchange Rate Policy & Capital Controls	1.05	0.80	1.00	1.20	0.34
International Trade Policy	0.89	1.43	0.36	0.38	0.01
Foreign Stock Markets	0.98	1.04	5.21	6.20	0.10
Terrorist Attacks & Non-State Violence	0.46	0.96	0.72	0.83	0.11
Unknown & No Explanation	17.42	10.54	10.58	9.79	8.82
No Article Found	0.42	0.00	1.68	13.23	4.53
Total	1,179	377	656	6,214	455

Figure 5: Jumps in the US Stock Market Are Mostly Due to US News, 1900-2023



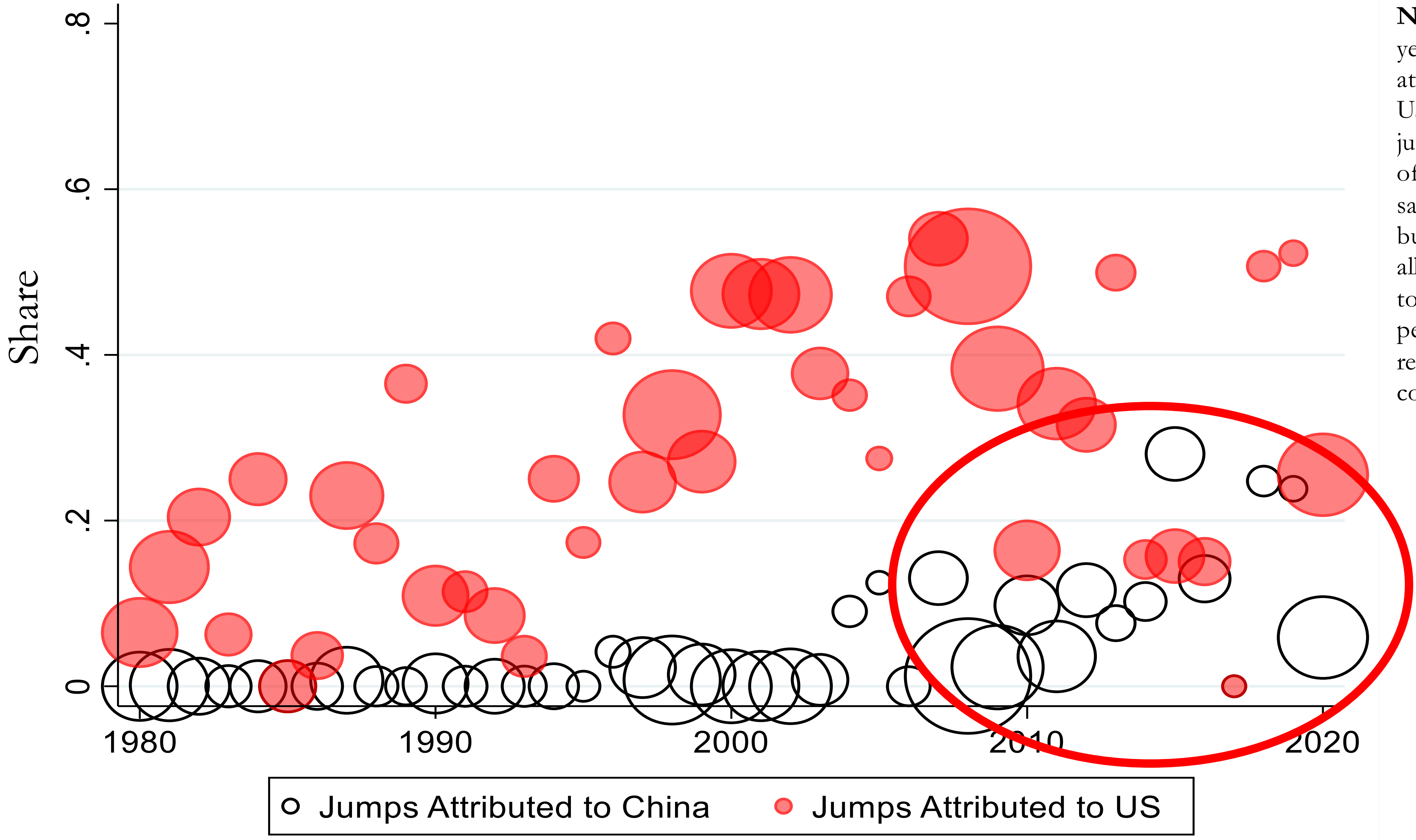
Notes: Dots show the yearly share of U.S. stock market jumps by the geographic origin stated at the top of the panel. Dot size reflects the number of jumps in that year. This chart excludes jumps classified as "Unknown or No Explanation Offered" and "No Article Found," which have no geographic attribution. There are no US jumps in 2023.

Figure 6: News about the United States Triggers a Large Share of National Stock Market Jumps in Other Countries, a Pattern that Does Not Hold for Europe



Notes: This chart shows the yearly share of jumps attributed to U.S. and Europe-related news (including news about individual European countries and supranational European institutions) in other countries, e.g., Brazil, China, India, and Japan. The sample runs from 1980 to 2020. Table A1 reports the sample period by country. Dot size is proportional to the average number of jumps per country in the year. The US share of global GDP is 19.3% and the average European share of global GDP is 27.1%. We calculate these shares using PPP-adjusted data for 1980-2016 from the International Monetary Fund.

News about China Triggers Few Jumps in the National Stock Market Jumps of Other Countries before 2005 and a Sizable Share from 2010 Onwards



Notes: This figure shows the yearly share of daily jumps attributed to the US outside the US and the yearly share of daily jumps attributed to China outside of China and Hong Kong. The sample runs from 1980 to 2020 but does not cover all countries in all years. Dot size is proportional to the average number of jumps per country in that year. Table A1 reports the sample period by country.

How Upward & Downward Jumps Differ

1. Among jumps triggered by policy developments, upward moves outnumber downward ones in every country. Downward moves are much more prevalent among jumps triggered by non-policy news.
2. The preponderance of upward moves among policy-driven jumps is entirely due to news about monetary policy and government spending.
3. For the roughly one-sixth of all jumps across all countries attributed to MP and GS, upward moves are more than twice as common as downward ones.
   - For US jumps attributed to monetary policy and government spending, the ratio of upward to downward moves is 2.3.
   - For US jumps attributed to Sovereign Military & Security Actions, in contrast, the ratio is only 0.5. For those attributed to Regulation, it is 0.8.
4. The greater the jump-day return, the greater the share of jumps attributed to monetary policy or government spending. See next two slides.

Table A3: Policy-Driven Jumps Tilt Upward in Every Country

	Non-Policy		Monetary Policy		Government Spending		All Policy	
	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive
Australia	67	20	2	9	5	15	13	31
Brazil	168	135	21	43	11	26	79	129
Canada	180	88	12	19	7	17	32	43
France	146	82	25	37	1	11	50	65
Germany	170	97	13	28	8	16	48	69
Greece	44	19	3	9	13	27	33	49
Hong Kong	108	72	8	17	7	15	42	56
India	62	37	8	13	4	12	42	60
Indonesia	59	26	8	16	3	11	36	51
Ireland	165	101	7	18	13	19	45	64
Japan	120	78	6	17	9	21	36	61
South Korea	116	82	6	15	5	22	43	81
New Zealand	25	9	0	1	0	1	0	2
Singapore	105	74	7	8	4	15	23	32
South Africa	127	82	9	18	6	14	29	48
Spain	179	101	24	55	26	38	92	124
Turkey	87	42	6	8	4	6	58	59
UK	215	135	21	40	18	30	98	128
US	325	217	28	62	22	55	192	234
All	2,467	1,496	212	431	165	370	991	1,385

Notes: Table entries report jump counts based on U.S. data from 1900 to 2023, U.K data from 1930 to 2023 and data for other countries from 1980 to 2020. This table excludes jumps classified as “Unknown or No Explanation Offered” and “No Article Found”.

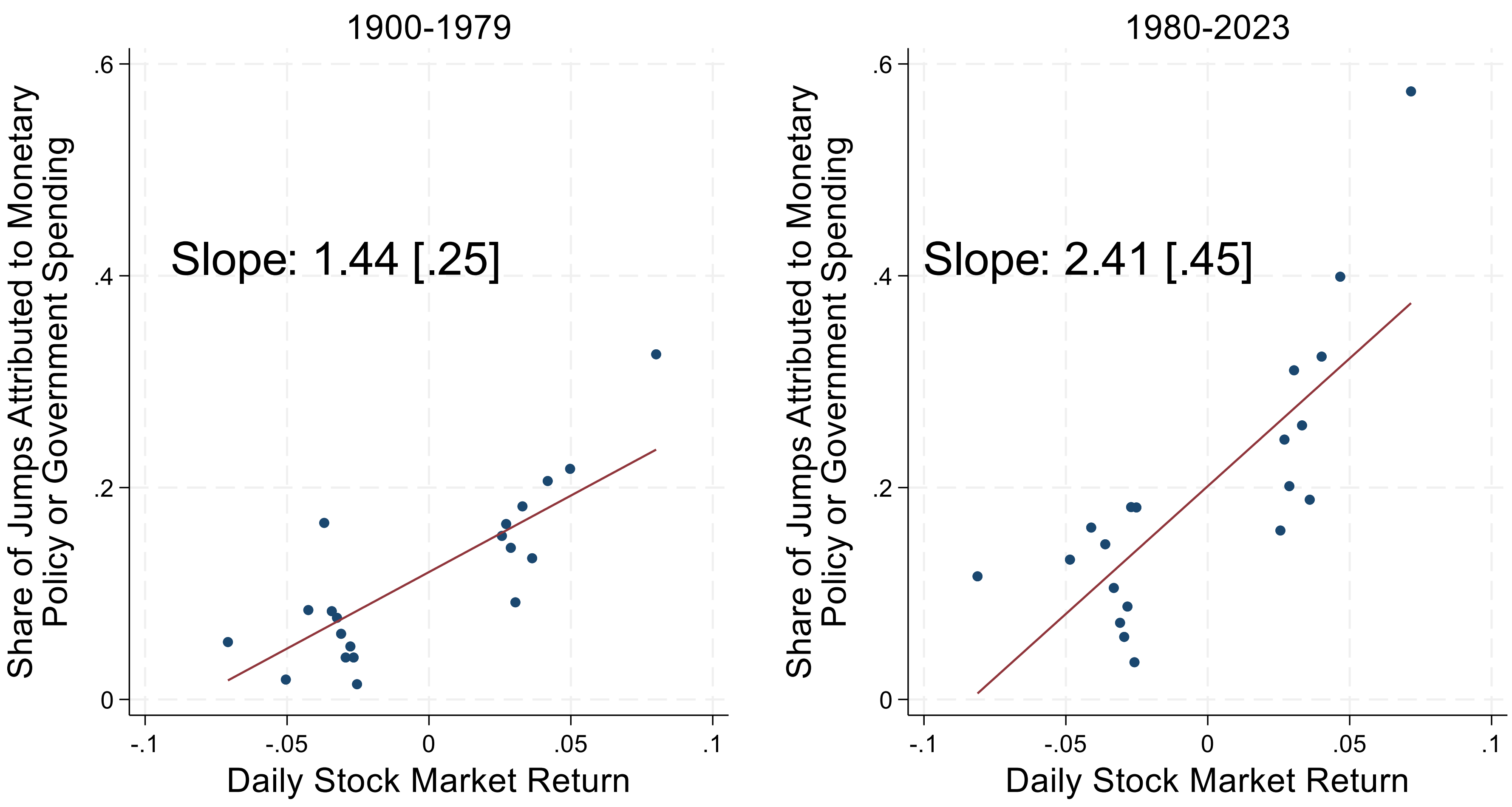
Table A4: Upward and Downward Jump Counts by Reason in the United States

	1900-1979		1980-2023		Post-1980	p-Value
	Positive	Negative	Positive	Negative	Return Shift	
Policy	**161**	**152**	**74**	**40**	**0.021**	**0.001**
Sovereign Military & Security Actions	33	65	5	6	0.011	0.416
Monetary Policy & Central Banking	30	16	33	12	0.010	0.275
Government Spending	36	12	18	10	-0.010	0.462
Regulation	20	25	2	1	0.006	0.857
Taxes	7	9	4	0	0.042	0.007
All Other Policy	34	26	12	10	0.003	0.818
Non Policy	**134**	**185**	**83**	**140**	**-0.022**	**0.000**
Macroeconomic News & Outlook	68	79	47	84	-0.024	0.000
Corporate Earnings & Outlook	33	44	25	30	0.002	0.846
Commodities	24	34	2	5	-0.017	0.358
All Other Non-Policy	8	27	9	22	0.007	0.571

Notes: Table entries report the number of negative and positive jumps in the indicated categories by era. The column labeled post-1980 return shift reports the coefficient on the interaction term (b_3) in the regression:

$$r_t = a + b_1 1_{t\in 1980-2023} + b_2 1_{t\in Category} + b_3 1_{t\in 1980-2023} \times 1_{t\in Category} + e_t$$

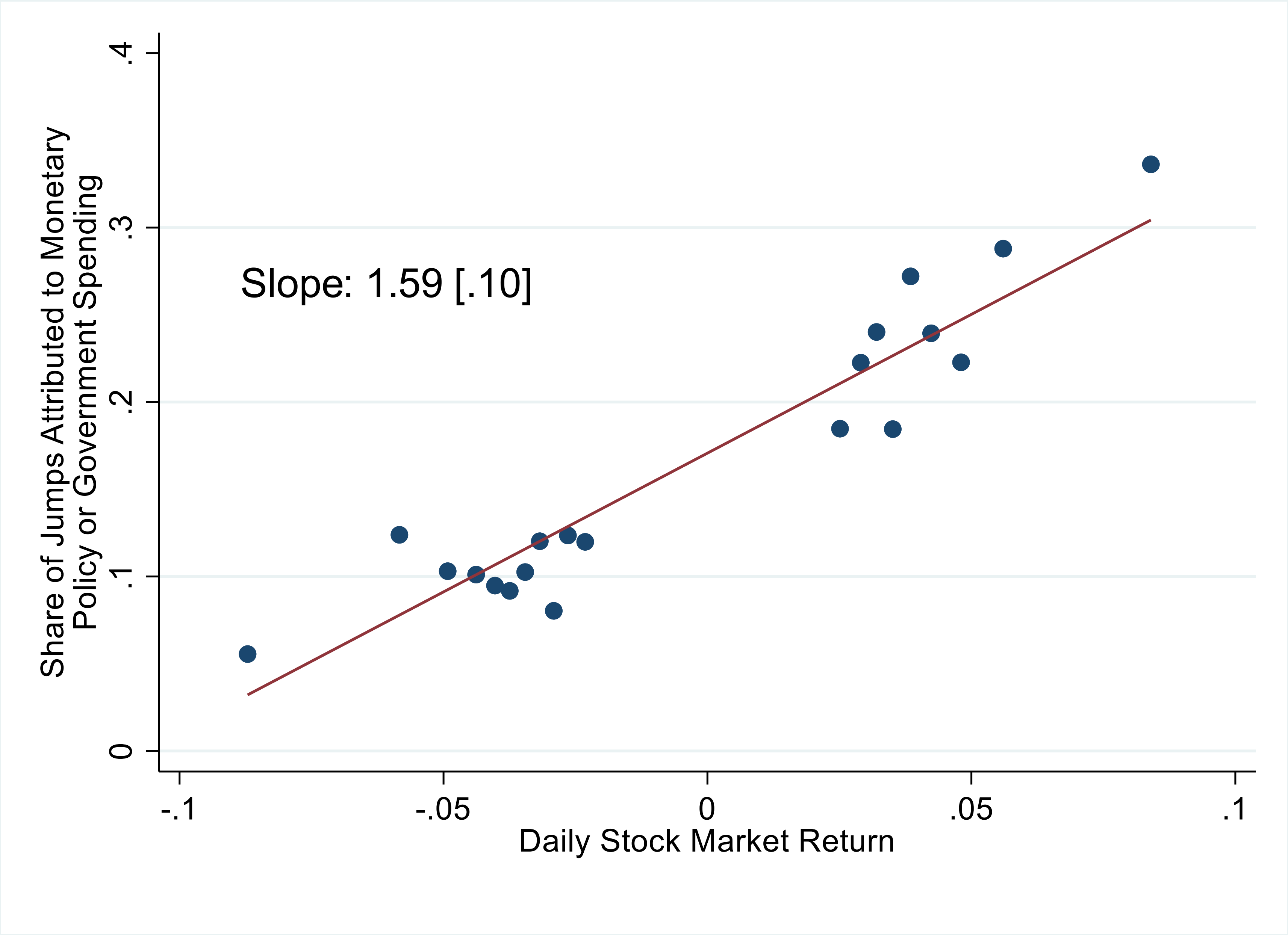
Figure 7: Monetary Policy and Government Spending Trigger A Larger Share of Upward than Downward Jumps in the U.S. Stock Market, More So After 1980



Notes: Each panel shows a bin scatter (n=20) of $MP_t + \mathrm{GS_t}$ on jump-day returns, where MP_t is the fraction of the jump's codings attributed to Monetary Policy & Central Banking, and GS_t is the fraction attributed to Government Spending. We obtain the fitted line in each panel by regressing $MP_t + \mathrm{GS_t}$ on the jump-day return, as measured by the CRSP value-weighted index, using jump-day observations. We plot the fitted regression line and report the slope coefficient [standard error] for each indicated sample period. We also consider a pooled sample that covers all jump days from 1900 to 2023 and fit the following regression: $(MP_t + GS_t) = a + b\, jdr_t + c\, 1_{post80} + d\, jdr_t \times 1_{post80} + e_t$, where jdr_t is the jump-day stock market return. This regression yields a coefficient of 0.97 on the interaction term with a t-statistic of 1.90.

Difference in slopes: 0.97, t-stat: 1.90

Figure A6: Monetary Policy and Government Spending News Triggers a Larger Share of Positive than Negative Jumps from 1980 to 2020 in 17 Other Countries (Excluding the U.S. and U.K.)



Notes: The chart shows a binscatter (n=20) of jump-level monetary policy + government spending scores on jump-day stock returns from 1980 to 2020 for 17 countries (all countries except the United States and the United Kingdom). The monetary policy + government spending score is the fraction of the jump's codings attributed to news about monetary policy and government spending (dropping days with no article found). The slope and standard error are from a regression of these jump-level scores on a constant and jump-level returns.

Put-Like
Policy Behavior

Why are large daily stock market reactions to news about monetary policy and government spending so skewed to the upside?

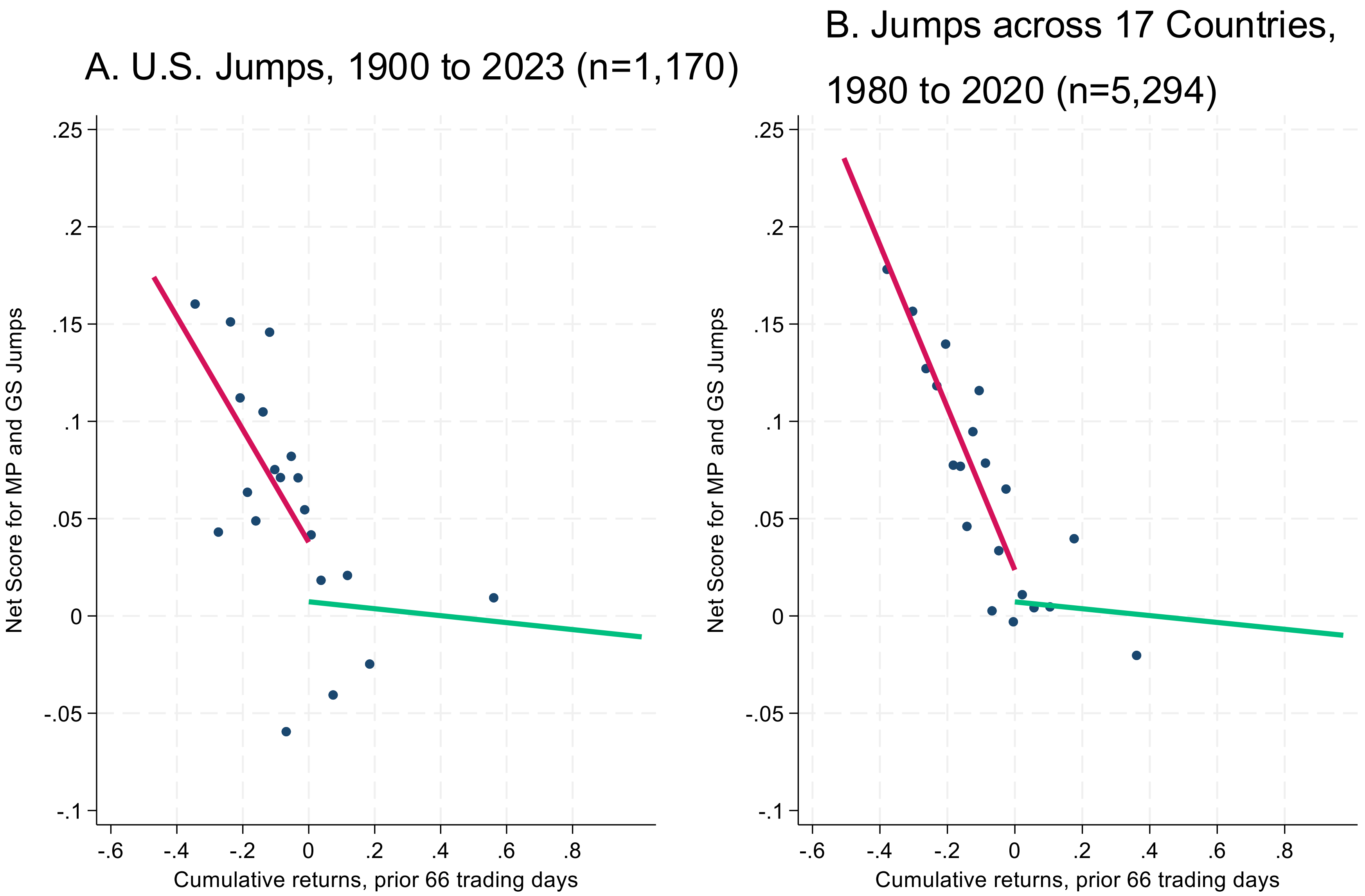
Hypothesis: Monetary and fiscal authorities seek to engineer positive shocks in reaction to a deterioration in market conditions, and they succeed more often than not. Motivating examples:

- Fed's liquidity support for the financial system after the October 1987 stock market crash
- Policy responses to the GFC by leading monetary and fiscal authorities around the world
- ECB's reaction to Euro-area sovereign debt crises in early 2010s
- Aggressive policy responses by monetary and fiscal authorities to the coronavirus pandemic of 2020-21

Assessing the Hypothesis

- Let MP_t be the share of codings attributed to Monetary Policy & Central Banking for a jump that occurs on day t.
  - If all readers attribute the day-t jump to monetary policy, then $MP_t = 1$. If half do so, then $MP_t = 0.5$.
- Let GS_t be the share attributed to Government Spending.
- $NET(MP_t + GS_{\mathrm{t}}) =$ sum of MP_t and GS_t for upward jumps and minus one times the sum for downward jumps.
- We relate $NET(MP_t + GS_{\mathrm{t}})$ to own-country stock market performance over the prior 66 trading days (three months).

Figure 8: Low Stock Returns over the Preceding 66 Trading Days Foreshadow Upward Jumps Attributed to Monetary Policy and Government Spending



Notes: These charts show bin scatters of jump-level $NET(MP_t + GS_t)$ values on own-country market returns over the prior 66 trading days. $NET(MP_t + GS_t)$ equals the share of codings attributed to monetary policy or government spending for upward jumps and (-1) times that share for downward jumps. Panel A covers U.S. jumps from 1900 to 2023. Panel B covers jumps from 1980 to 2020 in 17 of the 19 countries covered by our sample. We exclude jumps for which we could not locate a next-day newspaper article. Including them has little impact on the pattern shown. The two excluded countries, Brazil and Turkey, do not exhibit the same pattern. See Figure A8.

Three features of Figure 8 that warrant attention:

1. Most data points are in the upper left quadrant: Jumps attributed to MP or GS are more likely after the stock market falls <u>and</u> are typically in the upward direction.
2. The greater the stock market drop in the preceding 66 trading days, the greater the likelihood of an upward jump attributed to monetary policy or government spending.
3. Market gains in the preceding 66 trading days do <u>not</u> lead to jumps attributed to monetary policy or government spending.

Note: Data for Turkey and Brazil don't exhibit these patterns.

Table 4: The Put-Like Character of Jumps Triggered by MP and GS

Dependent variable: $NET(MP_t + GS_\mathrm{t})$

A. U.S. Sample, 1990 to 2023	Gov. Spend + Monetary		Government Spending		Monetary Policy	
	Jump Days	All Days	Jump Days	All Days	Jump Days	All Days
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Return Past 66 Trading Days * 1[Negative Return]	-0.291**	-0.142***	-0.131	-0.060***	-0.160*	-0.082***
	(0.127)	(0.025)	(0.097)	(0.020)	(0.083)	(0.015)
Cumulative Return Past 66 Trading Days * 1[Positive Return]	-0.018	-0.001	-0.029	0.001	0.011	-0.002
	(0.082)	(0.013)	(0.065)	(0.011)	(0.050)	(0.008)
1[Positive Return]	-0.030	0.004**	0.009	0.002	-0.039*	0.002**
	(0.030)	(0.002)	(0.019)	(0.001)	(0.022)	(0.001)
Intercept	0.038*	-0.004***	0.014	-0.002*	0.024	-0.002***
	(0.021)	(0.001)	(0.014)	(0.001)	(0.016)	(0.001)
Observations	1,170	33,474	1,170	33,474	1,170	33,474
R-squared	0.016	0.01	0.003	0.004	0.016	0.006

Column (1) mirrors the U.S. bin scatter exactly. It tells us how jump attributions relate to prior market performance, ***conditional on a jump occurring***.

More interesting: How prior market performance relates to ***unconditional jump likelihoods***. To address this question, we expand the sample to include all trading days in Column (2), setting $NET(MP_t + GS_\mathrm{t})$ to zero on non-jump days.

Quantifying Put-Like Policy Behavior

Conditional on a Jump Happening (Column 1)

- A 20 percent drop in the US market raises $NET(MP_t + GS_{\mathrm{t}})$ by 5.8 percentage points. This effect dwarfs the mean value of $NET(MP_t + GS_{\mathrm{t}})$ on jump days, which is only 0.2 ppts.

Effect on Unconditional Jump Likelihood (Column 2)

- A 20 percent market drop raises $NET(MP_t + GS_{\mathrm{t}})$ by 2.8 ppts.
- = 81% of unconditional jump likelihood (regardless of reason or direction)
- = 173% of unconditional likelihood of upward jump (regardless of reason).
- = 5.7 times the unconditional likelihood of any jump triggered by monetary policy or government spending.

More on Put-Like Policy Behavior

1. Put-like behavior holds for monetary policy and fiscal policy separately and is similar in magnitude for MP and GS. See Columns (3) to (6).
2. Very similar results, qualitatively and quantitatively, hold in the 17-country sample from 1980 to 2020. See Table 4 Panel B.
3. Put-like policy responses have strengthened over time in the US and UK, the two countries for which we have long-span data. Se Table A5.
   – UK and US results for period since 1980 imply that a 20% market drop raises the unconditional likelihood of a jump triggered by MP or GS by a **factor of ten**.
   – Suggesting that US and UK monetary and fiscal authorities have become more adept (or aggressive) at engineering positive news shocks in the wake of stock market drops.

Differences in Post-Jump Volatility by Jump Reason

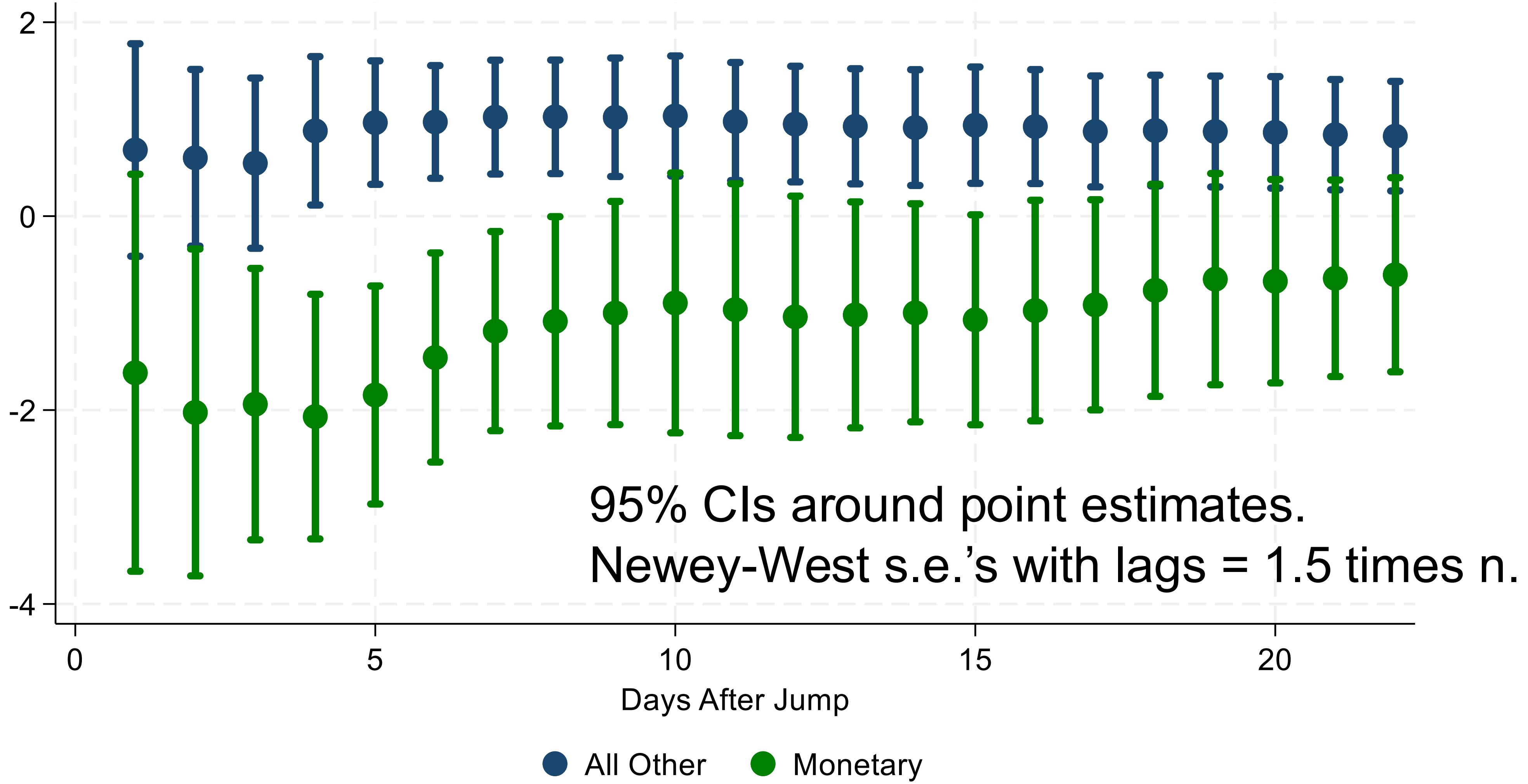
Chief finding: *Jumps triggered by news about monetary policy foreshadow much less post-jump volatility than other jumps. They even foreshadow a material decline in absolute volatility.*

Fit regressions of the following form to U.S. data from 1900 to 2023:

$$\sum_{i=1}^{n} \frac{r_{t+i}^2}{n} = a + b\left(r_t \times 1_{r_t>0}\right) + c\left(|r_t| \times 1_{r_t\leq 0}\right) + d\left(r_{t-1}^2\right) + e\left(\sum_{i=1}^{5} r_{t-i}^2\right) + f\left(\sum_{i=1}^{22} r_{t-i}^2\right) + g\, MP_t + h\left(Other_t\right) + e_t,$$

- r_t is the return on day *t* in the CRSP value-weighted index.
- Dependent variable: Realized daily volatility over *n* days after *t*.
- MP_t = share of codings attributed to Monetary Policy & Central Banking on day *t* for jump days, and zero otherwise.
- Define $Other_t$ analogously for the collection of other jump reasons.
- The omitted category is days with no jump.
- Control for return sign on day *t* (Black, 1976) and so-called "HAR" variables that capture past volatility over multiple look-back horizons (Corsi, 2009).

Figure 9: Volatility Is Lower after Monetary Policy Jumps than after Other Jumps, 1900-2023



At $n = 10$, for example, a jump triggered by news about monetary policy lowers the conditional forecast of stock market volatility by 2.17 (1.24 – (-0.93)) units relative to other jumps, where the units are average daily squared returns. This effect equals 78 percent of the average realized daily volatility over ten-day intervals in the US data.

- Jump-inducing news about monetary policy tends to dampen uncertainty – absolutely, and especially as compared to other jump-generating news.
- **An interpretation**: FOMC meeting announcements (and other Fed news about monetary policy) resolve prior uncertainty about whether the Fed will ease or tighten and, if so, by how much.
- This interpretation aligns with other evidence that FOMC meeting announcements tend to resolve uncertainty. For example:
    - Bauer et al. (2022) use high-frequency data on Eurodollar futures and options to construct a model-free measure of uncertainty about future short-term interest rates. They find that FOMC meeting announcements systematically reduce this measure of uncertainty, which then gradually ramps up again over the FOMC meeting cycle.
    - They also find that macro statistical releases don't systematically reduce short-rate uncertainty, which again aligns with our evidence.

Jump Clarity

1. Jump clarity rose a great deal over the past century.
2. Volatility is lower before and after high clarity jumps.
   - Clarity (and volatility) is positively autocorrelated.
3. Low-clarity jumps predict greater dispersion in firm-level equity returns.

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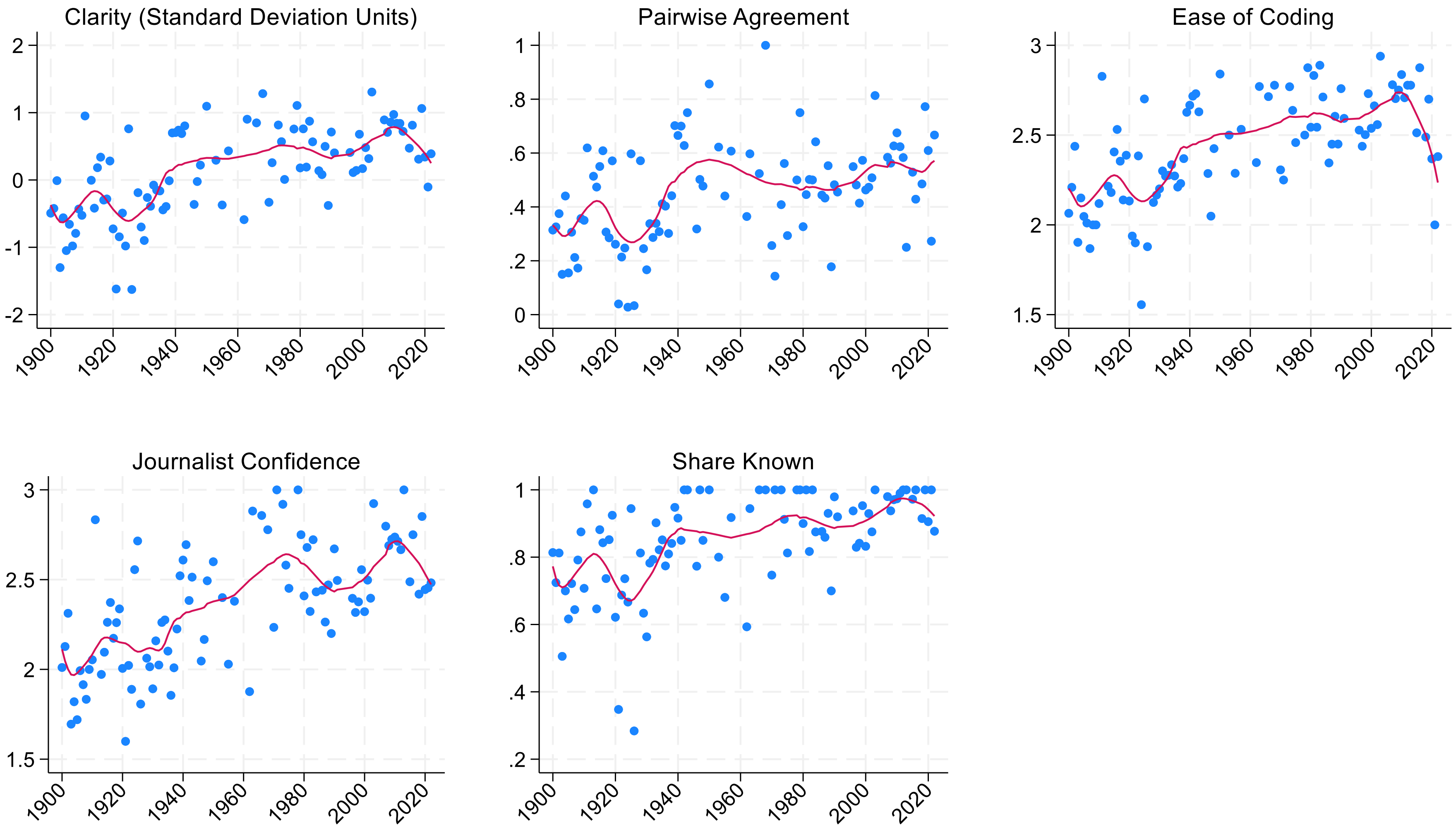
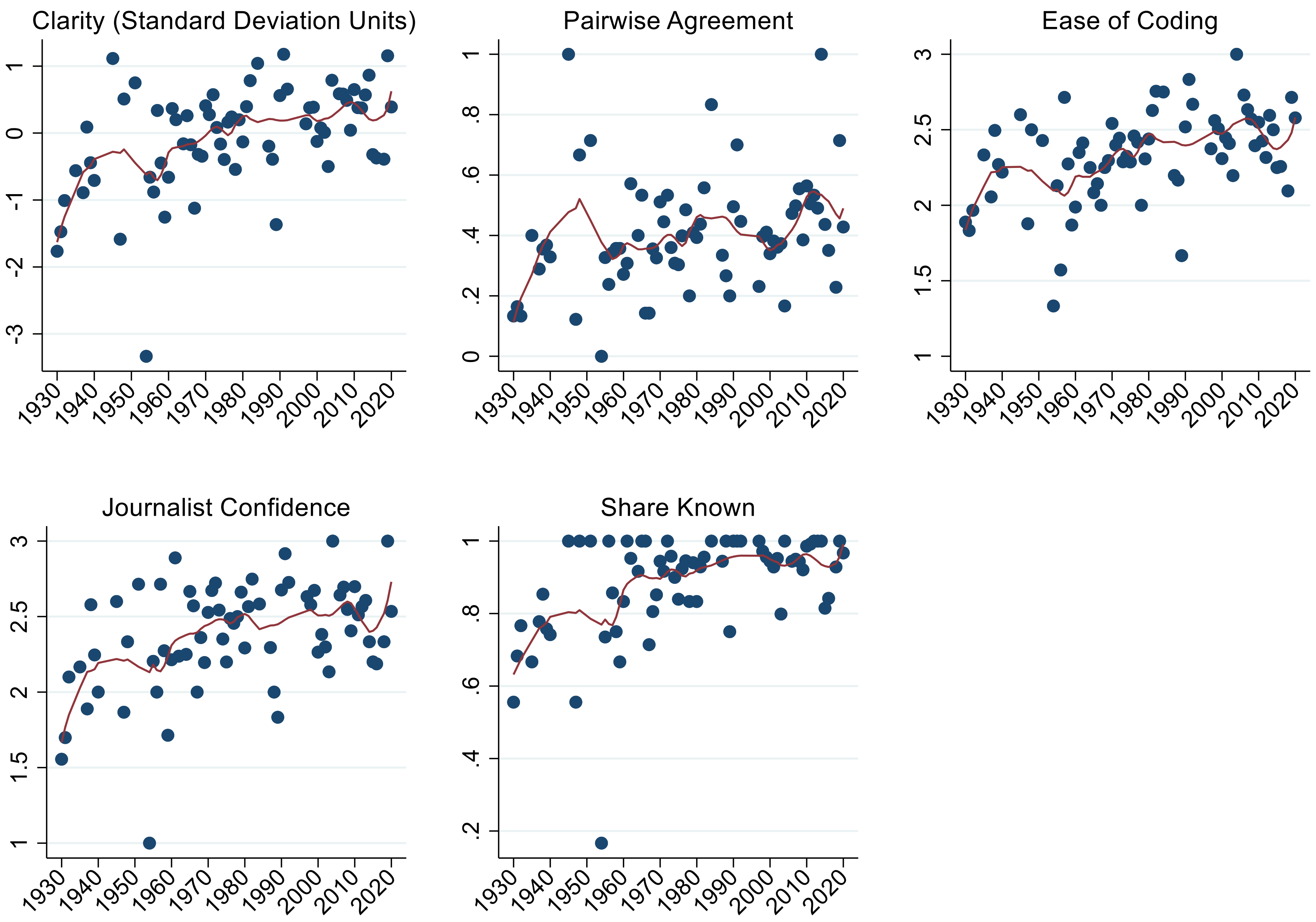
Figure 10: The Overall Clarity Index and Each Component Have Trended Towards Greater Clarity, U.S. Data, 1900-2022



Notes: The red line shows a LOWESS-smoothed fit with bandwidth set to 20 percent of the whole sample. Clarity is the sum of Ease of Coding, Journalist Confidence, Pairwise Agreement Rate, and the Share of Codings not attributed to "Unknown or No Explanation Offered" after each component is scaled to zero mean and unit standard deviation. Clarity is also scaled to have zero mean and unit standard deviation. There are no US jumps in 2023.

Ease of Coding is rated on a 1-3 scale, with 3 being the easiest. Journalist Confidence is rated on a 1-3 scale, with 3 being the most confident. Pairwise Agreement is the average pairwise agreement rate in the codings for a given jump. The median and mean number of coding pairs per jump is 36. Share Known is the percentage of codings for a given jump not coded as "Unknown or No Explanation Offered."

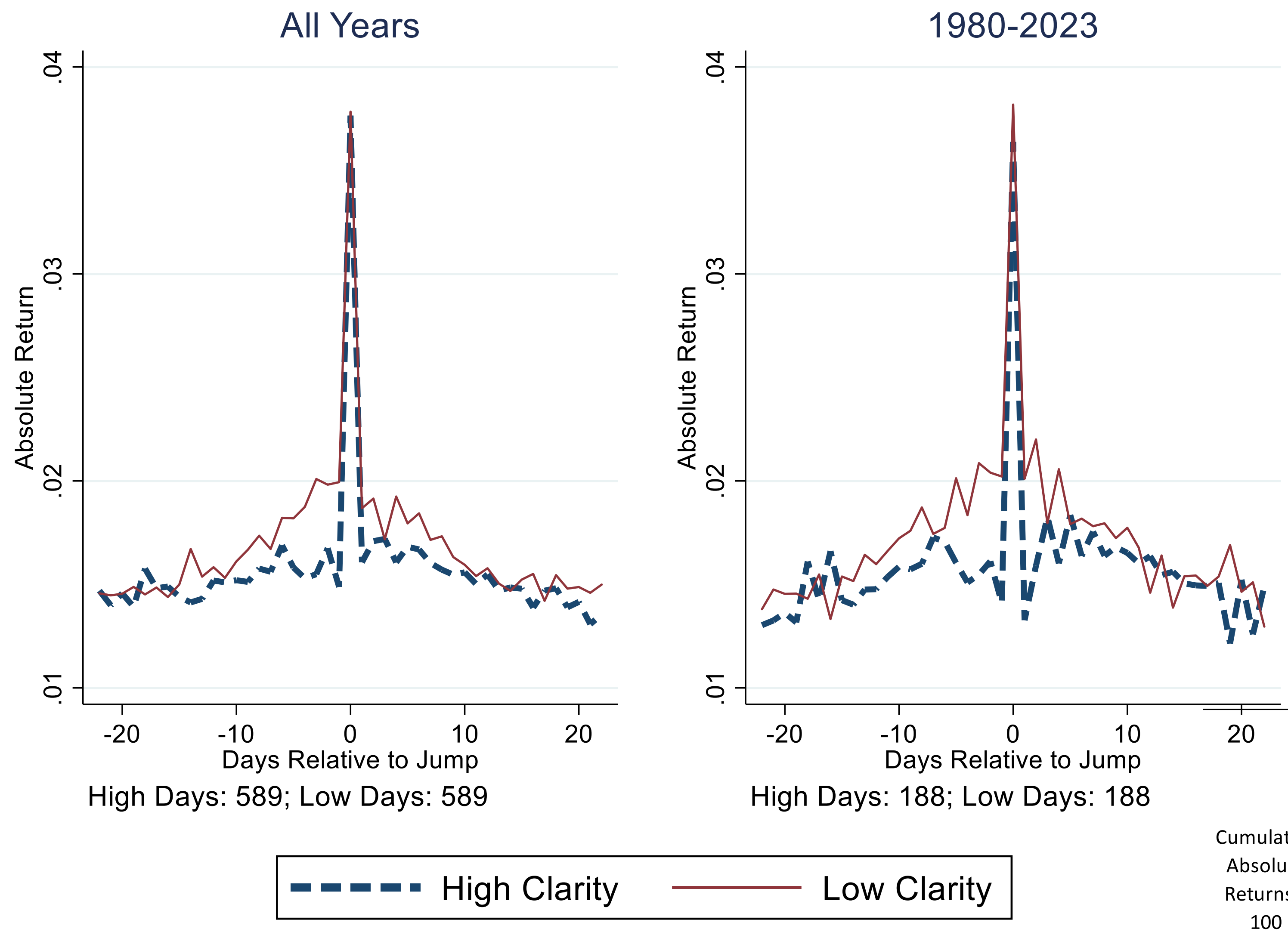
Figure A11: Clarity Index Components Over Time, UK Data, 1930 to 2020



Notes: Each red line shows a LOWESS-smoothed fit to the data, with a bandwidth set to 20 percent of the whole sample. Clarity is the sum of Ease of Coding, Journalist Confidence, Pairwise Agreement Rate, and the Share of Codings not attributed to "Unknown or No Explanation Offered" after each component is scaled to zero mean and unit standard deviation. Clarity is also scaled to have zero mean and unit standard deviation.

Ease of Coding is rated on a 1-3 scale, with 3 being the easiest. Journalist Confidence is rated on a 1-3 scale, with 3 being the most confident. Pairwise Agreement is the average pairwise agreement rate in the codings for a given jump. Share Known is the percentage of codings for a given jump not coded as "Unknown or No Explanation Offered."

Figure A10: Volatility is Lower Around High-Clarity Jumps, U.S. Data from 1900 to 2023



Notes: High (low) clarity is defined as clarity above (below) the sample median for either All Years (1900-2023) or 1980 onward. Each panel shows the average absolute return in a +/- 22-day window around jump days. The p-values are for t-tests of whether the mean absolute return in a +/- *n*-day window around the jump day differs between high-clarity and low-clarity jumps.

				Low Clarity	High Clarity	Low - High	p-value
Cumulative Absolute Returns x 100	1900-2023	Before	10-day	18.19	15.68	2.51	0.000
			5-day	9.68	7.82	1.86	0.000
			3-day	5.99	4.71	1.27	0.000
		After	3-day	5.50	5.04	0.46	0.046
			5-day	9.22	8.32	0.90	0.009
			10-day	17.74	16.27	1.46	0.016
	1980-2023	Before	10-day	18.87	15.87	2.99	0.017
			5-day	10.00	7.68	2.31	0.001
			3-day	6.15	4.57	1.58	0.001
		After	3-day	6.01	4.74	1.26	0.008
			5-day	9.86	8.18	1.67	0.018
			10-day	18.75	16.54	2.20	0.078

Why the Upward Drift in Clarity? 1

- Rising stock market capitalization raises demand for factual reporting and analysis of market-relevant news.
- The quality, scope, and timeliness of statistical information about the US economy have improved tremendously over the past century.
- Consider the BLS Monthly Employment Situation Report, which draws on the Current Employment Statistics (CES) and the CPS:
  - CES program began in 1915 as a sample of convenience of 200 large manufacturing firms.
  - BLS introduced formal sample design methods into the CES program around 1950
  - Followed by major sample design improvements in 1964, annual benchmarking to universe-level employment data in 1982, and the implementation of a probability-based sample design in 1995.
  - Sample sizes grew over time, reaching about 620,000 worksites in 2016.
  - CPS saw major improvements in data quality, scope, scale, and timeliness from the 1940s onwards.

→ The rich, high-quality, timely nature of the Monthly Employment Situation Report (and its predecessors) emerged over the past century or so. The same is true for many other government statistical releases.

Why the Upward Drift in Clarity? 2

- Information also became easier to access and cheaper to process.
- Jeon et al. (2022) point to the rise of the internet and the 1993 introduction of EDGAR, which offers free, searchable electronic access to SEC filings.
- Exploiting staggered rollout, Goldstein et al. (2023) find that EDGAR led to greater firm-level stock liquidity and more investment in listed firms.
- Gao and Huang (2020) find that EDGAR's implementation led to increases in volume and accuracy of information produced by sell-side analysts.

Advances over time in scale, quality, scope, timeliness, and accessibility of market-relevant information led to more understanding of market behavior among financial economists and market analysts.

→ Better factual and analytical foundation for journalists in their efforts to parse the often-complex drivers of stock markets for their readers.

Table 6: High-Clarity Jumps Predict Less Market Volatility and Dispersion in Firm-Level Returns

	Dependent Variable: Post-Jump Five-Day Volatility			Dependent Variable: Post-Jump Five-Day Average of the Cross-Sectional Standard Deviation of Firm-Level Returns,		
	(1)	(2)	(3)	(4)	(5)	(6)
Clarity Index	-4.339***	-4.213***	-1.751	-0.282***	-0.260***	-0.0969***
	(1.57)	(1.40)	(1.29)	(0.04)	(0.04)	(0.03)
Observations	1,177	1,177	1,177	987	987	987
R-squared	0.007	0.154	0.248	0.041	0.197	0.544
Controls	None	Returns	+HAR	None	Returns	+Past C-S St. Dev.
Sample Period	1900-2023	1900-2023	1900-2023	1926 to 2023	1926 to 2023	1926 to 2023

Notes: Each column reports a separate regression of the dependent variable on the Clarity Index. We compute the value-weighted cross-sectional standard deviation of firm-level returns using all ordinary common shares traded on major exchanges in CRSP. For columns 2 and 4, the controls are the jump-day market return, split into positive and negative components. For column 3, we add controls for the prior 1-day, 5-day and 22-day market-level returns volatility (HAR controls). For column 6, we add controls (relative to column 5) for the value-weighted daily cross-sectional standard deviation of firm-level returns, averaged over the 1-day, 5-day and 22-day period that precedes the jump day (i.e., three separate controls). A "day" refers to a trading day. The Clarity Index has mean zero and standard deviation one. The mean and standard deviation of the dependent variable in columns 1 to 3 are 32.4 and 52.5, respectively, after multiplying by 10,000. The mean and standard deviation of the dependent variable in columns 4 to 6 are 2.9 and 1.3, respectively, after multiplying by 100. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Summary of Key Findings

1. Jumps became more grounded in readily perceived news events over the past century.
2. News about the United States exerts an extraordinary influence on national stock markets around the world.
3. Jump properties differ systematically by jump reason. For example, news about monetary policy and government spending triggers a highly disproportionate share of all upward jumps.
4. The “Fed put” is but one manifestation of a broader phenomenon that extends to fiscal policy, operates across many countries, and emerged long before the 1990s in the US and UK.
5. Jumps attributed to monetary policy have high average clarity and foreshadow a ***drop*** in market volatility, unlike other jumps.

Directions for Future Research, 1

Policy Puts

- How is it that monetary and fiscal authorities manufacture upward stock market jumps twice as often as downward ones?
- How do they produce upward jumps at a **much higher** frequency after stock market crashes?
- It’s not obvious how to generate these patterns in models that feature rational agents and asset prices based on fundamental economic forces.
- Pástor and Veronesi (2012) develop perhaps the leading theoretical model of the interplay between stock prices and government policy.
  - In their model, stock prices fall on average at the announcement of government policy changes.
  - That’s opposite to what we find for stock market jumps triggered by monetary policy and government spending.

Directions for Future Research, 2

Clarity about what drives the stock market

- Our measurement approach opens the door to new studies of how the accuracy, depth, and timeliness of economic statistics affect clarity about the forces that drive stock market behavior.
- How does greater clarity about stock market drivers influence overall market volatility?
- How much does clarity matter for macroeconomic performance? Previous studies suggest that it matters a lot at the firm level.
- What is the social value of the statistical improvements that contribute to greater clarity about stock market behavior?

Directions for Future Research, 3

Distinguishing Discount Rate Shocks from Cash Flow News

- While central to asset pricing models, this distinction is often muddled in newspaper accounts.
- Integrating this distinction into our newspaper-based approach would require bringing in some combination of asset-pricing models and richer data.
- Previous work suggests many possibilities in this regard including:
  - The log-linearization of present value formulas as in Campbell and Shiller (1988).
  - More data-intensive approaches, as in Knox and Vissing-Jorgenson (2024) and Nagel and Xu (2024).

Directions for Future Research, 4

Applying NLP and Machine-Learning Tools

- A basic challenge: The sparsity of observations in distinctive jump categories that are occasionally important. For example, we find only ten US jumps attributed to trade policy developments from 1900 to 2023, half of them in 2018 and 2019. (Trump 2.0 is rapidly expanding this count.)
- Thin samples undercut the feasibility of the nonparametric methods and train-test-refine protocols typical of supervised machine learning.
- Frontier language models have achieved some success in zero-shot or few-shot classification tasks in some settings, but they are not yet capable of executing the highly granular and nuanced distinctions that we implement.
- Language models continue to improve, and we welcome efforts to develop a more automated approach. To that end, our human-generated data can serve as an essential testing ground for automated methods.

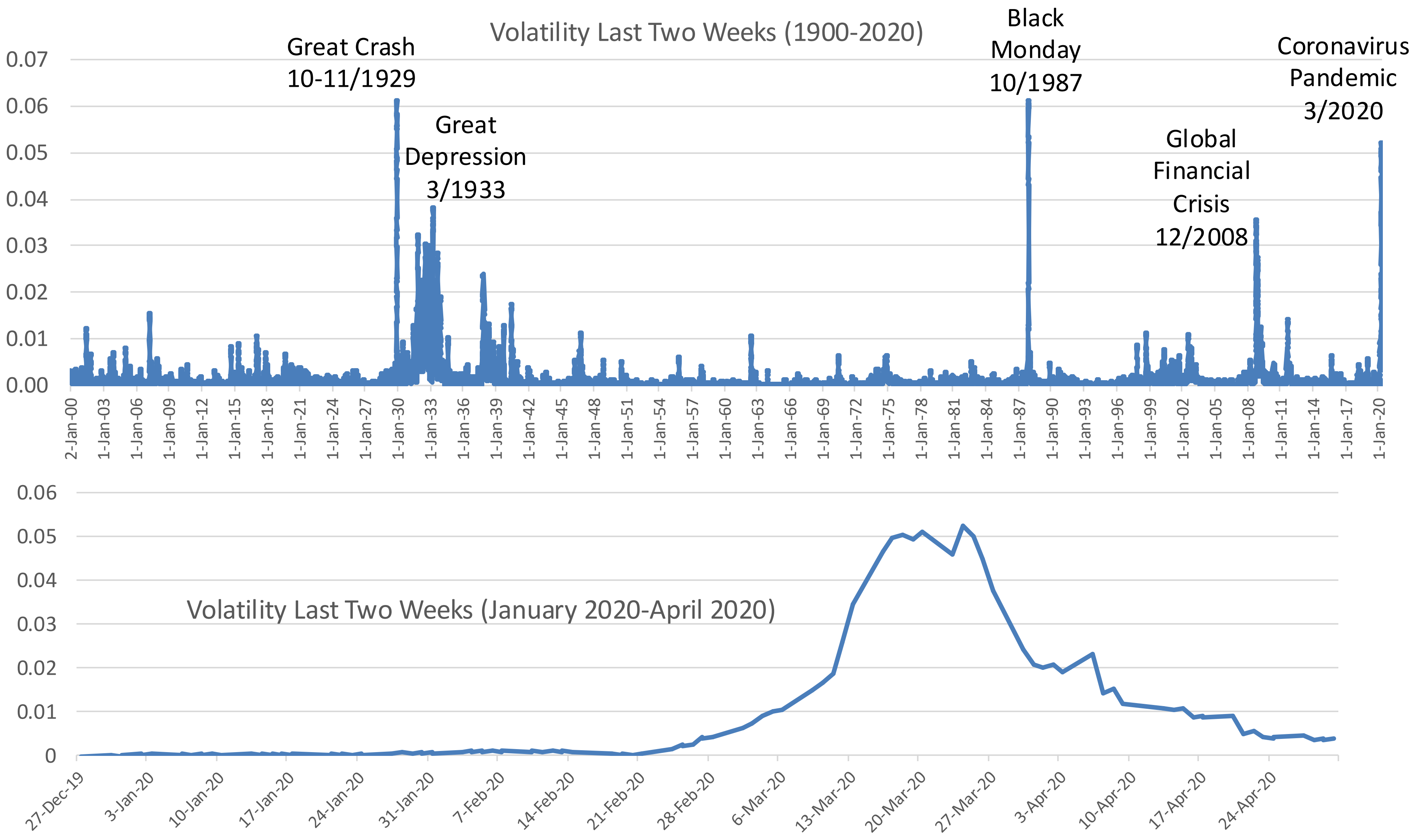
Macro Shocks and Firm-Level Response Heterogeneity

Davis, Hansen and Seminario-Amez

2020-2022: An Extraordinary Epoch

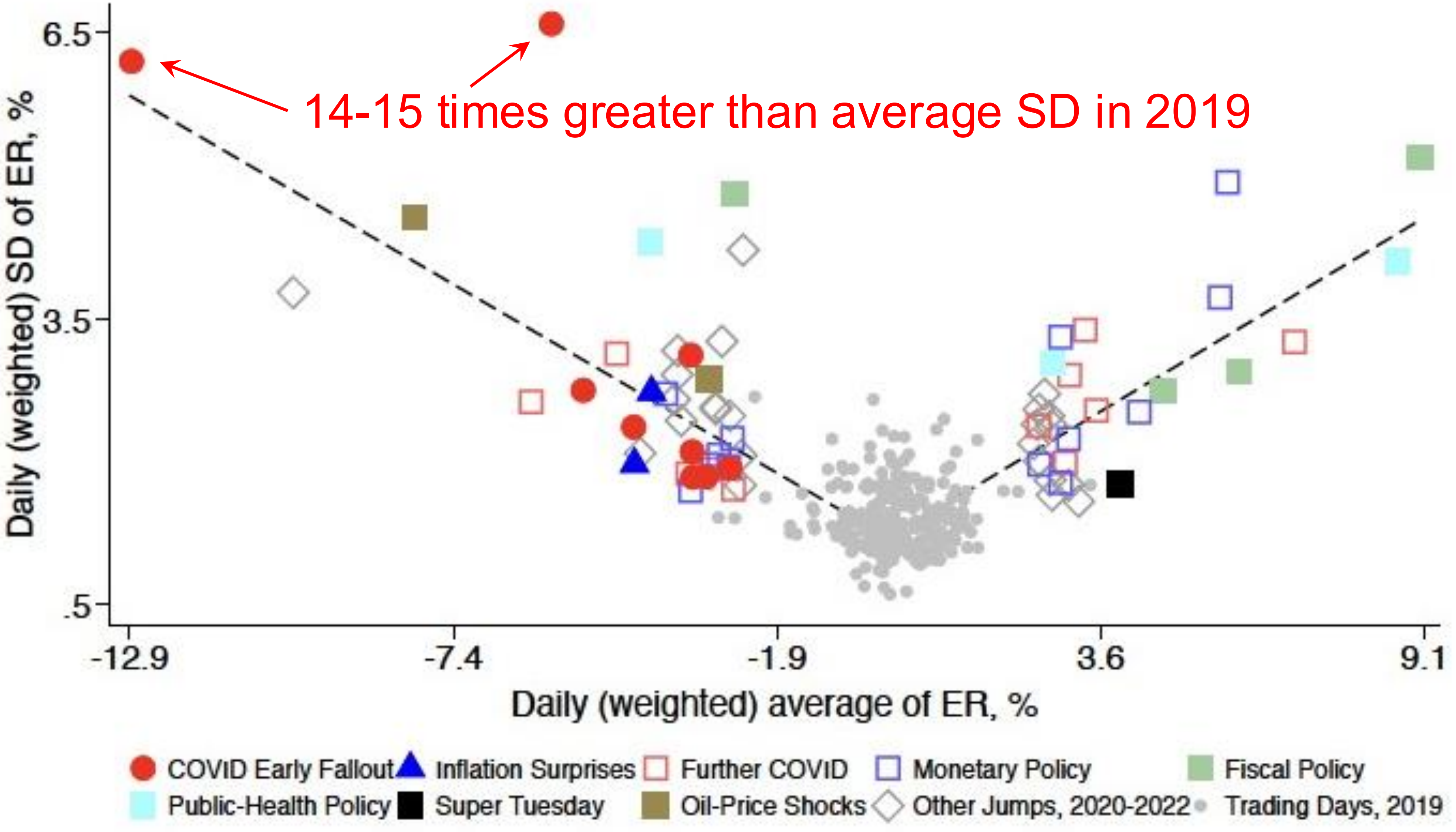
- **A Huge Flow of Macro Shocks:** Pandemic news, lockdowns, monetary and fiscal policy responses, oil prices, vaccine news, inflation surprises, …
- Real GDP fell 8% in the United States and 11% in the Euro area in 2020Q2 (quarter-on-quarter basis) in reaction to the COVID pandemic and lockdowns.
- Consumer price inflation reached 8-9% in 2022 in the United States and Europe, the highest in 40 years.
- Stock market crash and recovery in 2020. Historically high levels of market-level volatility.
- **Huge dispersion in firm-level returns on jump days**.

Realized U.S. Stock Market Volatility, January 1900 to April 2020



Notes: The sample period runs from 1/2/1900 to 4/30/2020. From December 1925 onwards, returns are computed using Yahoo Finance's 'adjusted close' series for the S&P 500 (^GSPC). Before that, returns are from the Global Financial Data extension of the Dow Jones Index. In both panels, we calculate realized volatility as the sum of squared returns over the past 10 trading days. Reproduced from Baker, Bloom, Davis, Kost, Sammon and Virayosin (2020).

Mean and Dispersion of Daily Firm-Level Equity Returns, All Trading Days in 2019 (a typical year) and Jump Days from 2020 to 20202



What We Do

1. Identify (the nature of) macro shocks from 2020 to 2022 based on next-day newspaper accounts, following the "Jumps" paper.
2. Construct firm-level exposures to these macro shocks based on the "Risk Factors" text in their pre-pandemic regulatory filings.
3. Investigate how well these exposure measures explain the huge cross-firm dispersion of abnormal returns from 2020 to 2022.
4. Investigate how well exposure measures (based on pre-pandemic regulatory filings) explain the massive heterogeneity in firm-level growth rates after the pandemic hits.
5. Develop interpretable, text-based characterizations of how and why each firm is exposed (or not) to the identified macro shocks. (Not much covered in this lecture.)

Preview of Main Findings

1. Our text-based shock exposure measures greatly (and parsimoniously) improve on standard models in explaining the huge dispersion across firms in abnormal returns on jump days.
2. The part of abnormal returns explained by our text-based measures also explains ***future*** firm-level revenue growth, while the residual component of abnormal returns does not.
3. Our shock exposure measures explain most of the tremendous heterogeneity in firm-level revenue growth after the pandemic hits.
4. Countercyclical dispersion in firm-level growth rates arises from differences in firm-level exposures to macro shocks.
   – Because macro shocks differ across cyclical episodes the cross-firm response pattern also differs.

Text and Other Data Inputs

1. Daily U.S. market-level stock returns, jump dates, and jump-by-reason classifications as in "Jumps" paper.
2. Daily firm-level stock returns.
3. Firm-level data on market cap, leverage, NAICS
4. Each firm's discussion of its "Risk Factors" in 10-K filings from 2015-19. We use one compiled report per firm.
   – The RF text describes risks related to the firm's technologies, competitors, customers, suppliers, business model, workforce, government policies, geopolitical concerns, etc.
5. Merging 2, 3 and 4 yields an analysis sample of about 2,000 firms.
6. Linking in Compustat data on real-side business outcomes yields a balanced panel of about 1,000 firms.

U.S. Stock Market Jumps, February 2020 to December 2022

Category	Dates (MM/DD/YY)
COVID Early Fallout	02/24/20, 02/25/20, 02/27/20, 03/03/20, 03/05/20, 03/11/20, 03/16/20, 03/18/20, 03/26/2020, 03/27/2020
Super Tuesday	03/04/20
Oil-Price Shocks	03/09/20, 03/07/22
Public Health Policy	03/13/20, 03/20/20, 04/17/20
Fiscal Policy	03/10/20, 03/23/20, 03/24/20
Monetary Policy	03/02/20, 03/17/20, 04/22/22, 05/04/22, 05/05/22, 05/27/22, 06/10/22, 08/26/22, 11/02/22, 11/10/22, 11/30/22
Further COVID	03/30/20, 04/01/20, 04/06/20, 04/08/20, 04/14/20, 04/21/20, 04/29/20, 05/18/20, 06/05/20, 06/11/20, 06/24/20, 10/28/20
Inflation Surprises	05/18/22, 09/13/22
Other Categories	02/25/21, 03/01/21, 03/09/22, 03/16/22, 04/26/22, 04/29/22, 05/09/22, 05/13/22, 06/13/22, 06/16/22, 06/24/22, 07/19/22, 07/27/22, 10/03/22, 10/04/22, 10/07/22, 10/17/22, 12/15/22

To keep the presentation (and paper!) to a reasonable length, I will focus on jumps in two categories: "Early COVID Fallout" and "Inflation Surprises". Our methods apply equally well to other jump categories.

Returns and Outcomes: A Suggestive Example

Average abnormal return on "Early COVID Fallout" jump days relative to a standard CAPM model with controls for market cap, leverage, and NAICS2.

Company	NAICS	Abnormal Return[1]	Revenue Growth 2018Q3-2020Q3
NetApp Inc	3341[2]	4.34%	-6.9%
Scientific Games	3341	-4.92%	-64.2%
Domino's Pizza	722511[3]	-0.04%	20.8%
Ruth's Hospitality Group	722511	-9.28%	-44.5%

- Large abnormal return differences within same 4-digit NAICS in response to COVID news shocks in February-March 2020.
- Abnormal return differences correlate with later revenue growth.
- We use RF text to explain the abnormal return differences ***and*** to build better predictors of future firm-level revenue growth.

Constructing Firm-Specific Shock Exposures

We apply the multinomial inverse regression approach of Taddy (2013, 2015). Gentzkow et al. (2019) is a well-known application.

Step 1: Fit multinomial regression models for the expected frequency of each term in a firm's RF report as a function of the firm's abnormal return on jump days (of a given type) and other firm observables.

- The full RF corpus contains about 20 millions words across all firms with about 14,000 unique terms or "features."
- RF report word counts: Mean $\approx$11,000, and St. Dev. $\approx$ 7,000

Step 2: Obtain a "sufficient reduction projection" – **a firm-specific scalar value** – that summarizes the textual information about the firm's abnormal return response to the given macro shock.

- This quantity, which varies across firms and by jump types – serves as our measure of firm-specific shock exposures.

Multinomial Inverse Regression Approach, 1

- MNIR treats the *RF* texts for each firm as a *bag-of-words* represented by a *V*-dimensional vector of terms or ``features'' in machine-learning speak.
- $V \approx 14{,}000$, the number of unique terms in our *RF* corpus (after pre-processing).
- $c_{i,v}$ is the count of term *v* $\in V$ for firm i.
- $\boldsymbol{c}_i$ is the corresponding vector of counts for firm i.
- $C_i = \sum_v c_{i,v}$ is the total count of all terms *v* that appear in the RF report for firm i.
- $c_{i,v}$ / C_i = firm i's term-*v* count as share of its total count

Multinomial Inverse Regression Approach, 2

- MNIR posits that the count vector $\boldsymbol{c}_i$ is drawn from a multinomial distribution with probability vector $\boldsymbol{p}_i^d$, where d designates the jump day or jump type.
- Parametrize the vth element of the probability vector as

$$p_{i,v}^d = \frac{\exp(\eta_{i,v}^d)}{\sum_v \exp(\eta_{i,v}^d)} \quad \text{where} \quad \eta_{i,v}^d = \alpha_v^d + \beta_v^d \text{AbnRet}_i^d + \left(\gamma_v^d\right)^T \text{controls}_i^{y(d)}$$

where $\text{controls}_i^{y(d)}$ contains NAICS2, market cap and leverage (and the latter two are year-specific).

β_v^d captures how an increase in AbnRet_i^d on jump day *d* is associated with greater usage of term *v* in the firm's pre-pandemic RF text.

Multinomial Inverse Regression Approach, 3

We fit our multinomial logistic regression model over *V* terms to roughly 2,000 observations per jump day (or jump type), one per firm. Here, we model the probability that a particular term in *V* appears in a random draw from the firm's *RF* text.

We fit the regression using Bayesian regularization methods with a Gamma-Laplace prior structure on the regression coefficients. The prior trades off goodness-of-fit and model complexity, maximizing an information criterion to avoid over-fitting. See Taddy (2013, 2015) for details.

Multinomial Inverse Regression Approach, 4

- MNIR associates terms with abnormal returns but does not immediately yield a scalar value for the firm's shock exposure.
- To obtain such a measure, we use a **sufficient reduction projection** of the RF text. Specifically, firm i's exposure to the macro shock associated with jump date (or jump type) d is

$$z_i^d = \sum_v \hat{\beta}_v^d \frac{c_{i,v}}{C_i}$$

which is a weighted average of the estimated MNIR coefficients on returns, with weights given by term *v*'s share in the firm's RF term count. Hence, the more the firm uses terms associated with positive (negative) returns on *d*, the more positive (negative) its exposure to the macro shock in question.

Multinomial Inverse Regression Approach, 5

$$z_i^d = \sum_v \hat{\beta}_v^d \frac{c_{i,v}}{C_i}$$

is called a sufficient reduction projection because it contains all the information in the high-dimensional count vector $\boldsymbol{c}_i$ that is relevant for predicting AbnRet_i^d (conditional on controls).

So, we can use it as a low-dimensional representation of $\boldsymbol{c}_i$ that captures the association between pre-pandemic business characteristics, as stated in the RF texts, and the jump-date returns for the macro shock in question.

Ranking of Terms for Pandemic Dates

Bottom Terms		Top Terms	
Term	**Value**	**Term**	**Value**
hotel	-33549.80	game	19595.17
unitholder	-18019.33	product_candidate	18475.38
general_partner	-14038.83	client	17157.35
gaming	-11840.90	drug_candidate	12859.84
restaurant	-11830.94	clinical_trial	11963.56
reit	-10605.63	cellular	9029.67
tenant	-10177.66	subscription	7706.73
satellite	-9343.81	solution	7571.91
crude_oil	-9220.05	patient	6222.35
common_unit	-9087.59	student	6058.91
hotel_property	-8337.83	platform	5430.79
refinery	-7749.49	drug	5120.28
travel	-6931.05	collaborator	4641.59
franchisee	-6722.54	datum_center	4317.81
trs	-6657.09	celgene	4266.25

Table: **Influential Terms for Pandemic Jumps**. The ranking of term v is based on its tf-idf score multiplied by $\hat{\beta}^P_v$.

Ranking of Terms for Inflation Dates

Bottom Terms		Top Terms	
Term	**Value**	**Term**	**Value**
tenant	-15810.95	hotel	31389.56
student	-9557.59	natural_gas	9899.49
operating_partnership	-7896.48	gaming	8074.73
reit	-7610.02	crude_oil	8016.95
real_estate	-7081.87	hotel_property	7193.75
homebuilding	-7078.13	aircraft	7111.44
the_company	-7038.95	solar	7065.24
product_candidate	-6580.21	pipeline	6868.64
home	-6515.21	oil	6852.39
client	-6057.50	ferc	6846.26
property	-5597.77	unitholder	6420.11
cellular	-5487.07	drilling	6027.62
fcc	-5200.31	ngl	5968.09
clinical_trial	-4671.19	fuel	5235.03
wireless	-4270.11	semiconductor	5142.39

Table: **Influential Terms for Inflation Jumps**. The ranking of term v is based on its tf-idf score multiplied by $\hat{\beta}^I_v$.

Abnormal Return Regressions (in the Cross Section)

To assess the marginal value of our text-based exposure measures in explaining cross-sectional return variation on jump dates, we estimate two abnormal return regressions and compare them with respect to goodness of fit.

$$\text{AbnRet}_i^d = \alpha_0^d + \left(\boldsymbol{\alpha}_1^d\right)^T \mathbf{controls}_i^{y(d)} + \epsilon_i^d$$

$$\text{AbnRet}_i^d = \gamma_0^d + \left(\boldsymbol{\gamma}_1^d\right)^T \mathbf{controls}_i^{y(d)} + \gamma_2^d z_i^d + \gamma_3^d C_i + \varepsilon_i^d$$

The second specification above adds the text-based exposure measure, z_i^d, and a control for the total count of terms, C_i, in firm i's RF text.

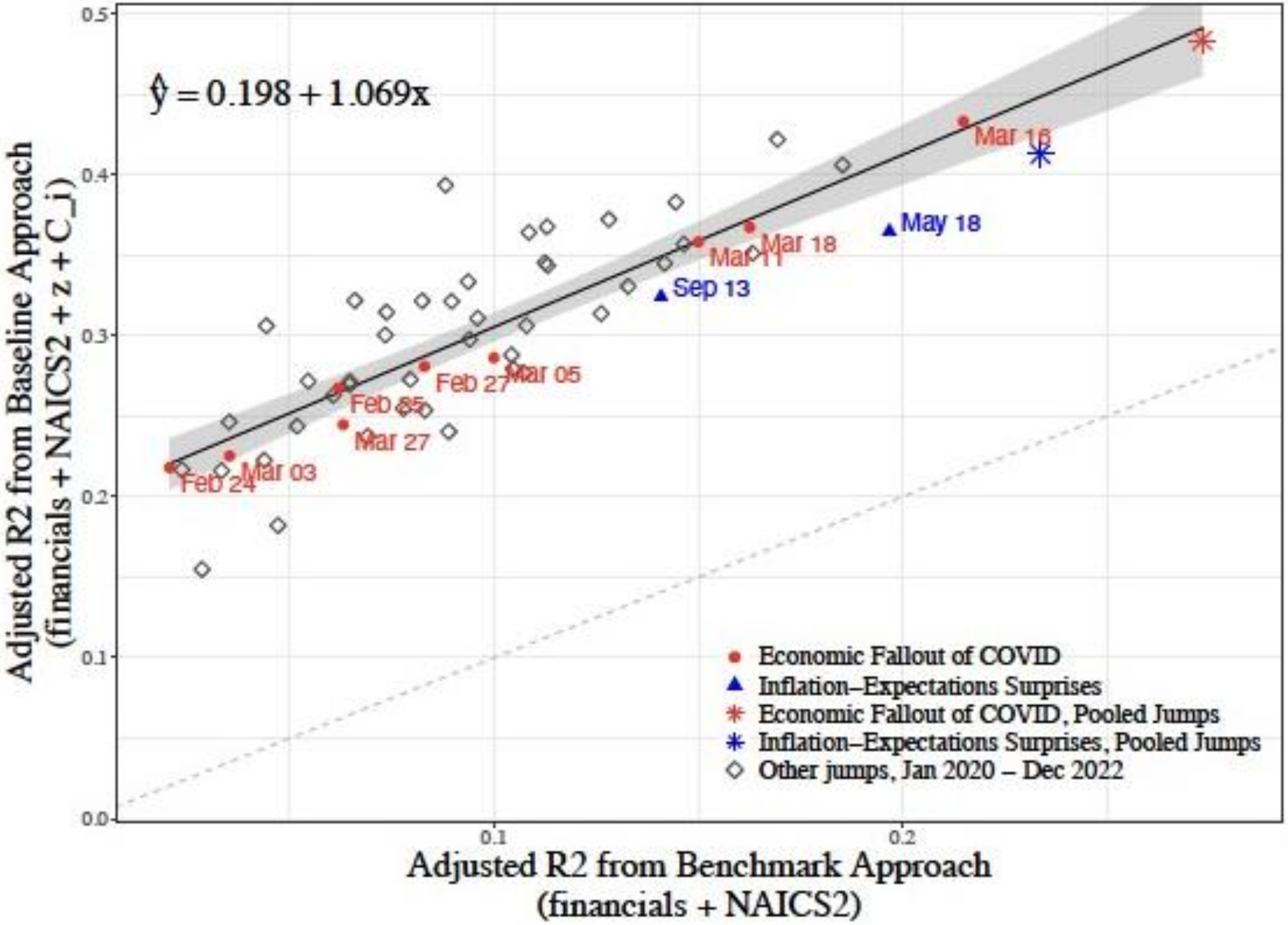
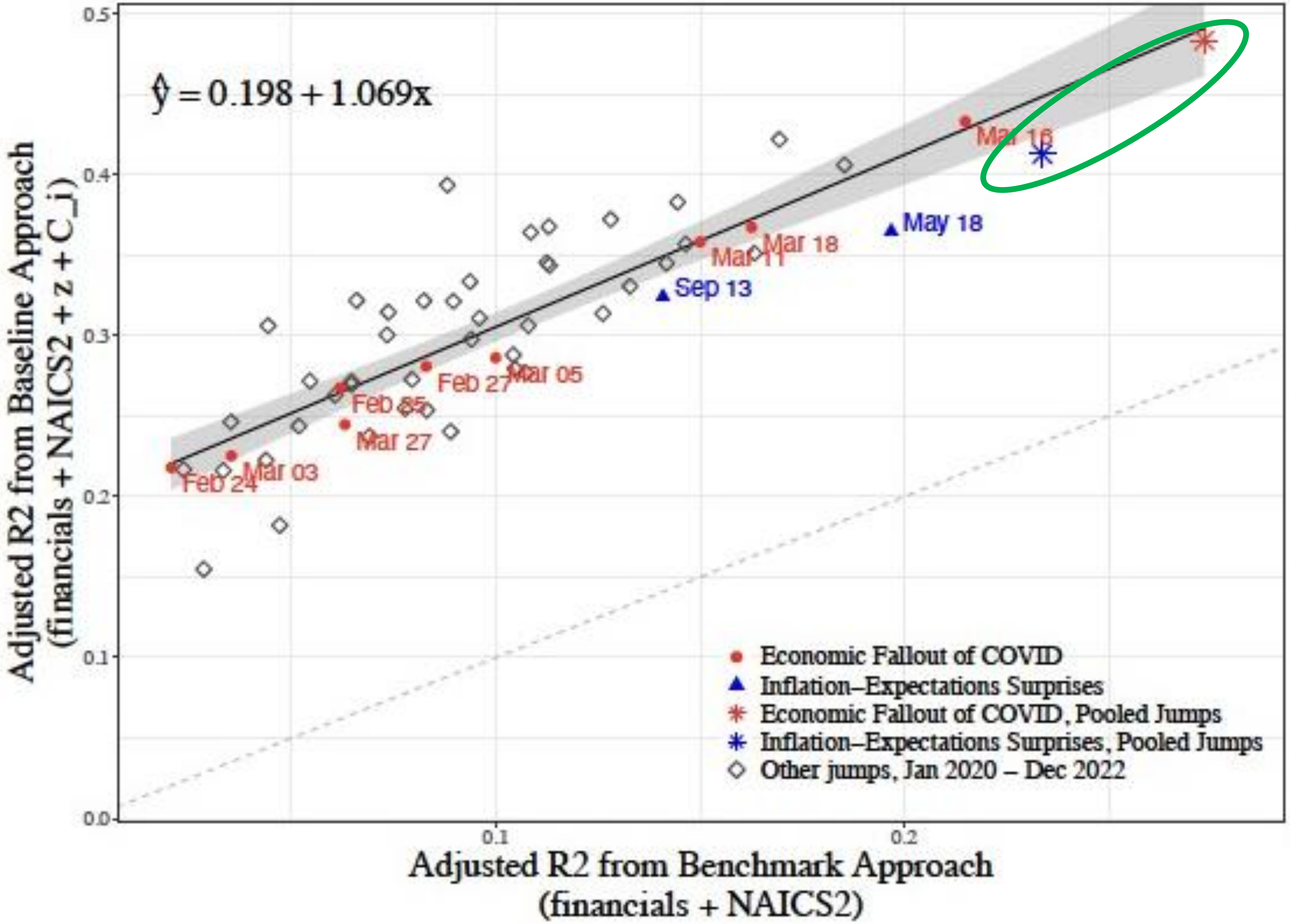


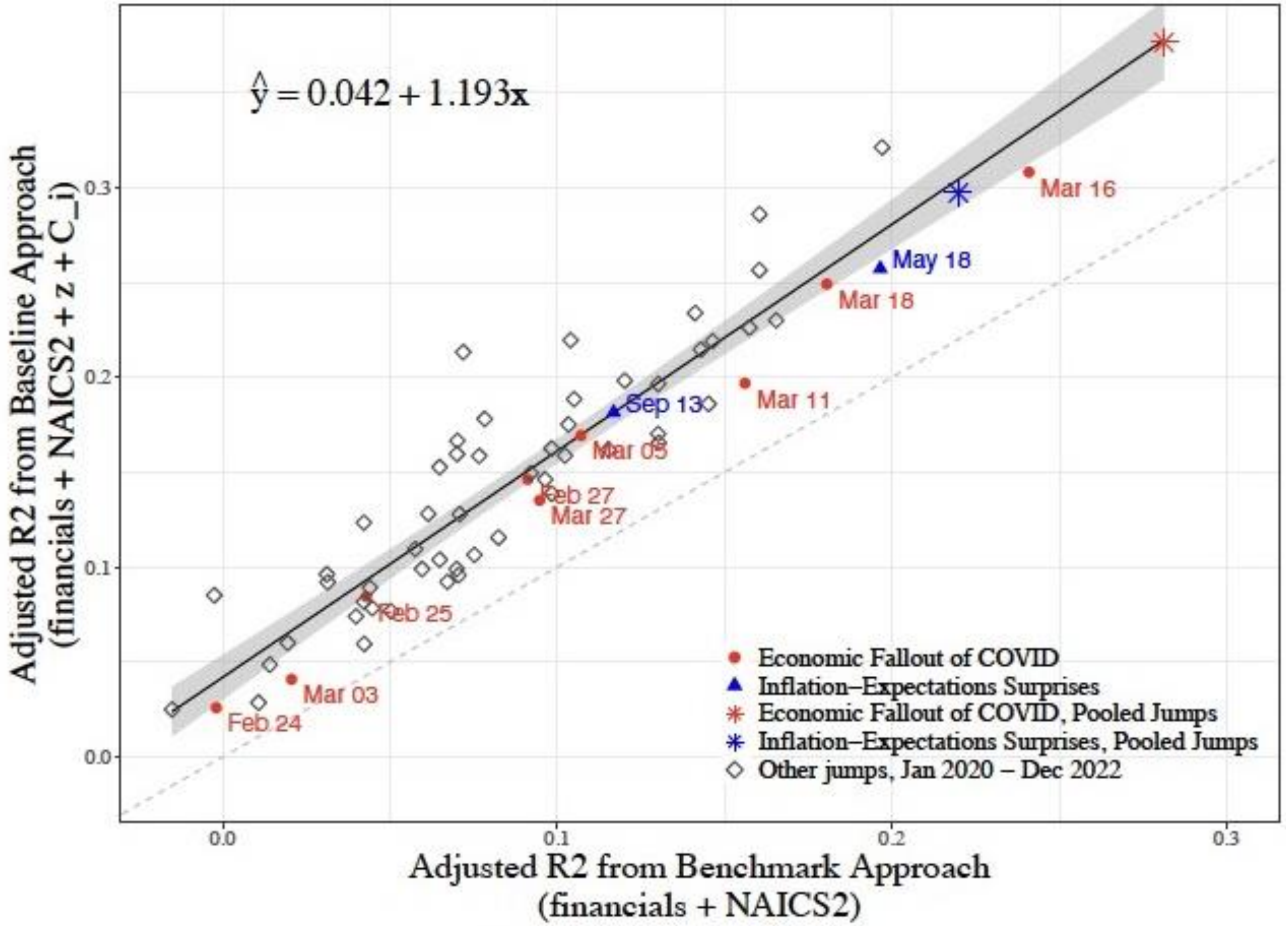
Figure: Adjusted R^2 from regressing abnormal returns from jump dates on controls for NAICS2 sector, leverage, and size (x-axis) and additionally including text-based shock exposures and controls for text length (y-axis).

Adding the "sufficient reduction projection" in the abnormal return regressions always yields a large gain in the adjusted R-squared value – roughly 20 ppts.



Pooling over all jumps of a given type raises the adjusted R-squared value above what is obtained when using any single jump day of a given type.

Figure: Adjusted R^2 from regressing abnormal returns from jump dates on controls for NAICS2 sector, leverage, and size (x-axis) and additionally including text-based shock exposures and controls for text length (y-axis).



(b) Out-of-Sample

Out-of-sample performance assessment, where the held-out sample contains other firms on the same dates

Figure 3: Improvement in Goodness-of-Fit from Including Text in Asset Regressions. These figures report the adjusted R^2 from regressing abnormal returns from jump dates on controls for NAICS2 sector, leverage, and size (x-axis) and additionally including text-based shock exposures and controls for text length (y-axis). The top panel uses the entire sample, while the bottom panel reports the adjusted R^2 on held-out firm samples not used for the estimation of the MNIR coefficients.

Out-of-sample performance assessment, where the held-out sample involves future jump dates for jumps of the same type.

	(1) Second Wave Fears (2020/06/11)	(2) Vaccine News (2020/05/18)	(3) Slower Fed Tightening (2022/11/10)
Exposure Variable	z_i^P	z_i^P	z_i^I
Coefficient	0.51***	-0.46***	-0.23***
	(0.032)	(0.060)	(0.026)
Observations	1,552	1,552	1,506
Adjusted R^2	0.349	0.339	0.116
Adjusted R^2 (only controls)	0.199	0.207	0.069

Table 1: Generalization of Text Exposures to Out-of-Sample Dates. We fit the forward regression (4) on selected dates using z_i^P or, alternatively, z_i^I as the text exposure The dates we select are not used to build the text exposures.

Do Firm-Specific Shock Exposures Explain Future Firm-Level Revenue Growth?

Main real outcome of interest is quarterly revenue growth

$$\Delta \text{rev}_{it} = \log(\text{rev}_{i,t}) - \log(\text{rev}_{i,t-12}) \quad t = 2018Q1, \ldots, 2022Q4$$

The use of twelve-quarter growth rates ensures that growth in each post-pandemic quarter in our sample is computed with respect to a pre-pandemic quarter.

We compare two approaches to explaining firm-level revenue growth:

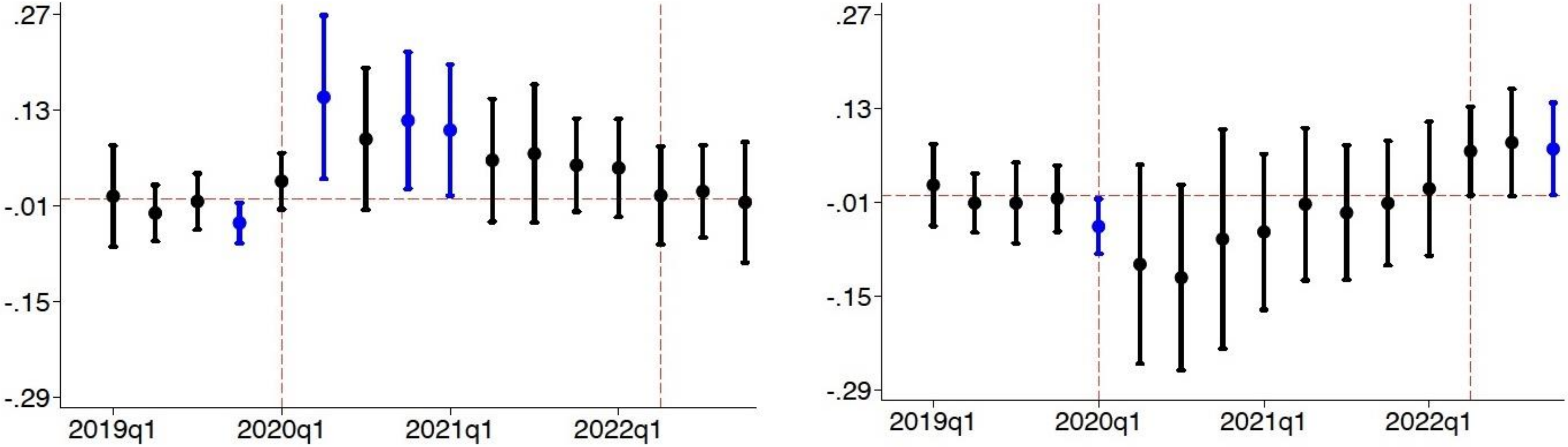
1. Using abnormal returns directly, in line with the literature.
2. Our text-based exposure measure + the part of abnormal return not explained by our our exposure measure (idiosyncratic part)

Revenue-growth regression specifications

$$\Delta \mathrm{rev}_{it} = I_i + I_{s(i),t} + \sum_{t=19Q1}^{22Q4} I_t \alpha_t{}' \mathbf{e}_i + \sum_{t=18Q1}^{18Q4} I_t \beta' \mathbf{controls}_{it} + \sum_{t=19Q1}^{22Q4} I_t \beta_t' \mathbf{controls}_{it} + \epsilon_{it} \quad (6)$$

- I_i are firm fixed effects, and the $I_{s(i),t}$ are NAICS2 × quarter fixed effects.
- $\mathbf{e}_i$ is a firm-level vector of shock-exposure measures.
- $\mathbf{controls}_{it}$ includes leverage and log assets in period $t - 12$.
- Because the coefficients on controls are constant during a baseline period (2018Q1 through 2018Q4), the β_t coefficients capture whether the association between controls and revenue growth shifts in quarter t relative to the baseline.
- The primary coefficients of interest are $\boldsymbol{\alpha}_t$ which describe the relationship between shock exposures and real outcomes in period t.
- $\boldsymbol{\alpha}_t$ reflects whether an increase in shock exposures induces a deviation of a firm's period-t growth rate from its baseline growth rate.

Using Abnormal Returns on *P* and *I* Days to Quantify Firm-Level Exposures



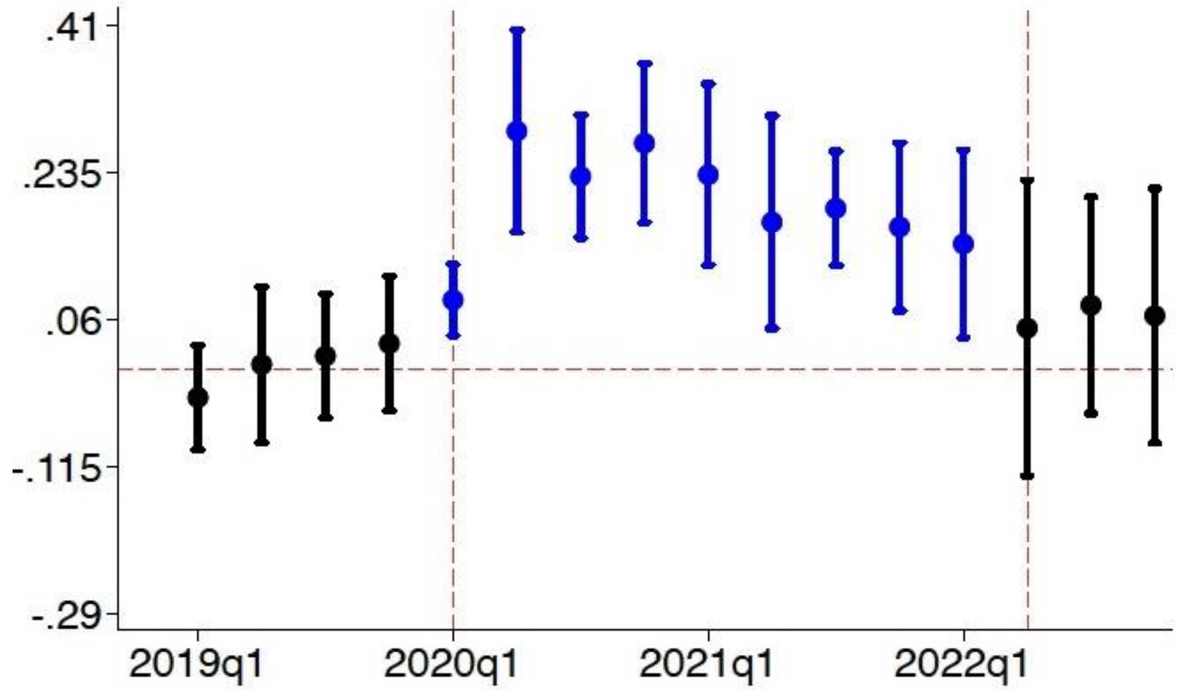
(a) Effect of Pandemic Exposure

(b) Effect of Inflation Exposure

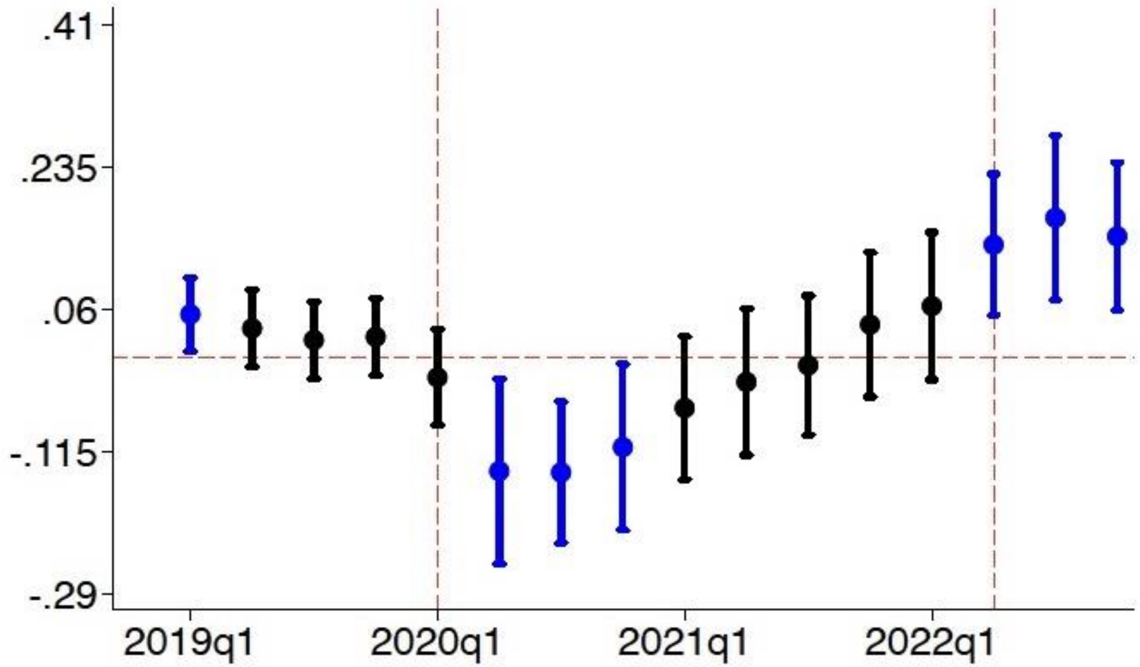
Figure 4: Effect of Shock Exposure (Returns) on Quarterly Revenue Growth.

This figure displays the estimated α_t coefficients from (6) when using exposure measures (EXP-RET) derived from abnormal returns on pandemic and inflation jump dates. Point estimates dispalyed with 95% confidence intervals.

Using Our Text-Based Measures for *P* and *I* Shocks to Quantify Firm-Level Exposures



(a) Effect of Pandemic Exposure

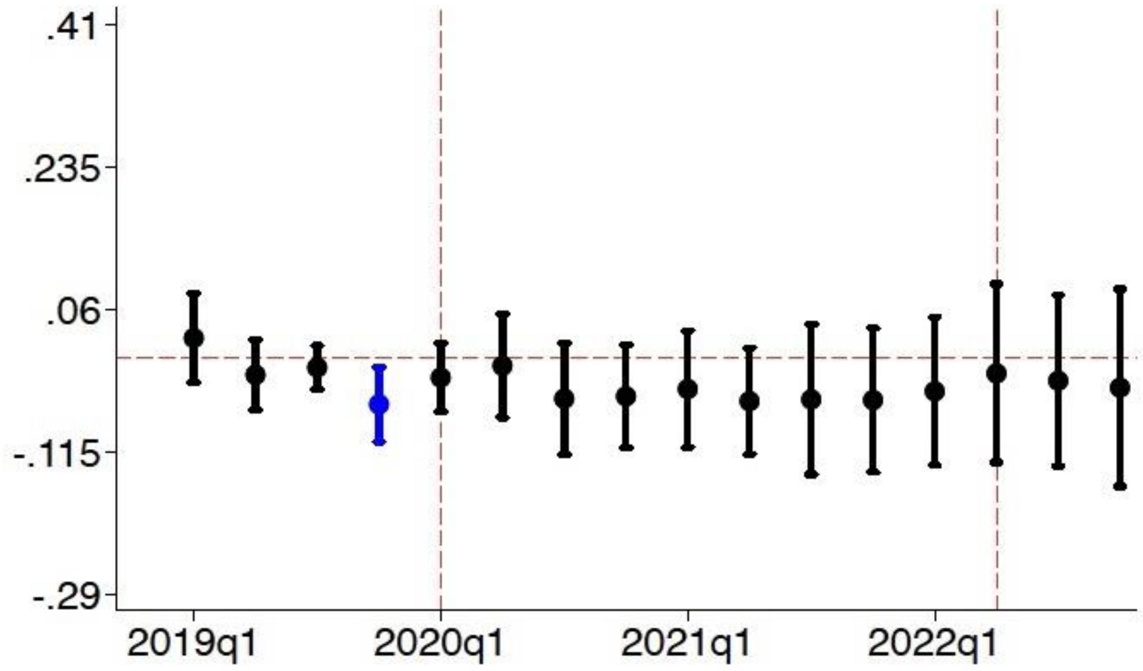


(b) Effect of Inflation Exposure

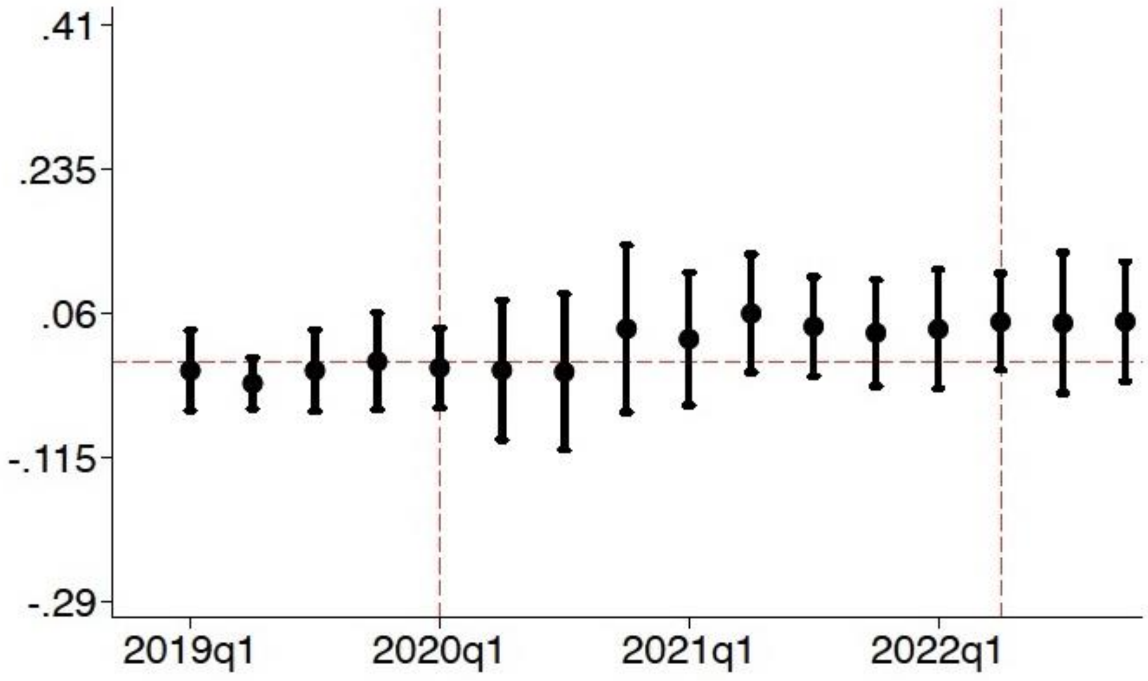
Figure 5: Effect of Shock Exposure (Text) on Quarterly Revenue Growth

This figure displays the estimated α_t coefficients from (6) when using (EXP-TEXT) as the vector of exposures. Top (bottom) panel displays coefficient on pandemic (inflation) text exposure. Point estimates dispalyed with 95% confidence intervals.

Using the Part of Abnormal Returns Not Explained by Our Text-Based Exposure Measures (Residual Component)



(a) Effect of Pandemic Exposure



(b) Effect of Inflation Exposure

Figure A.3: Effect of Shock Exposure (Residual) on Quarterly Revenue Growth

This figure displays the estimated α_t coefficients from (6) when using (EXP-TEXT) as the vector of exposures. Top (bottom) panel displays coefficient on pandemic (inflation) residual exposure. Point estimates dispalyed with 95% confidence intervals.

Text-Based Shock Exposures Account for Most of the Realized Dispersion in Revenue Growth Rates

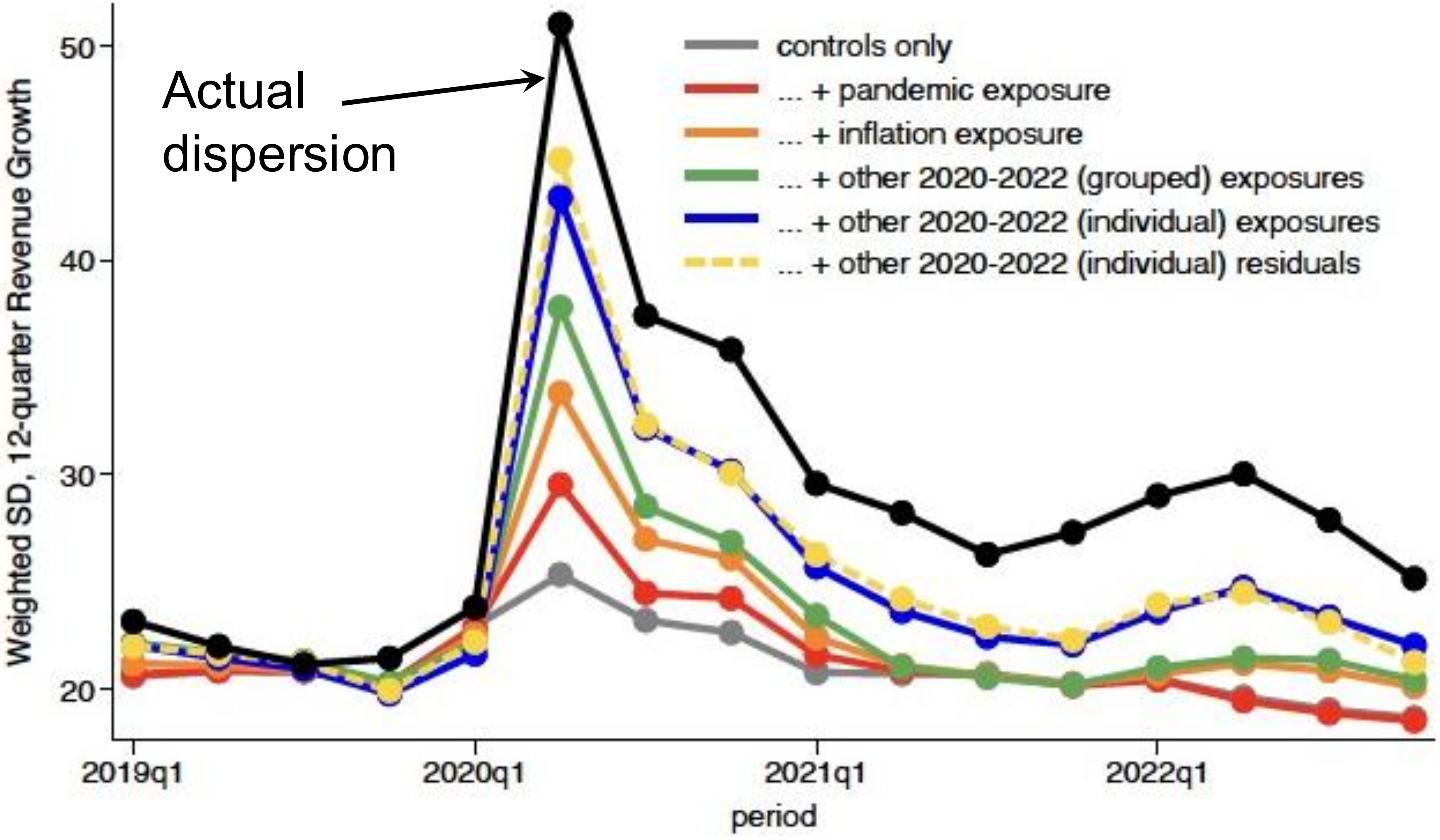


Figure: Realized and Fitted Standard Deviation of Revenue Growth

Historical Evidence on Countercyclical Dispersion in Firm-Level Growth Rates

- Does this characterization of countercyclical dispersion in firm-level growth rates hold more generally?
- 10-K filings with RF text in current form introduced in 2006. For many firms, the RF section was not fully developed by 2007 when the GFC began, the triggering event for the largest contraction prior to COVID-19.
- So, we can't directly assess the generality of this characterization.
- However, we can provide some indirect evidence.
- <u>First result</u>: Historically, jump frequency during recessions is three times greater than during expansions.
- <u>Second result</u>: Next slide

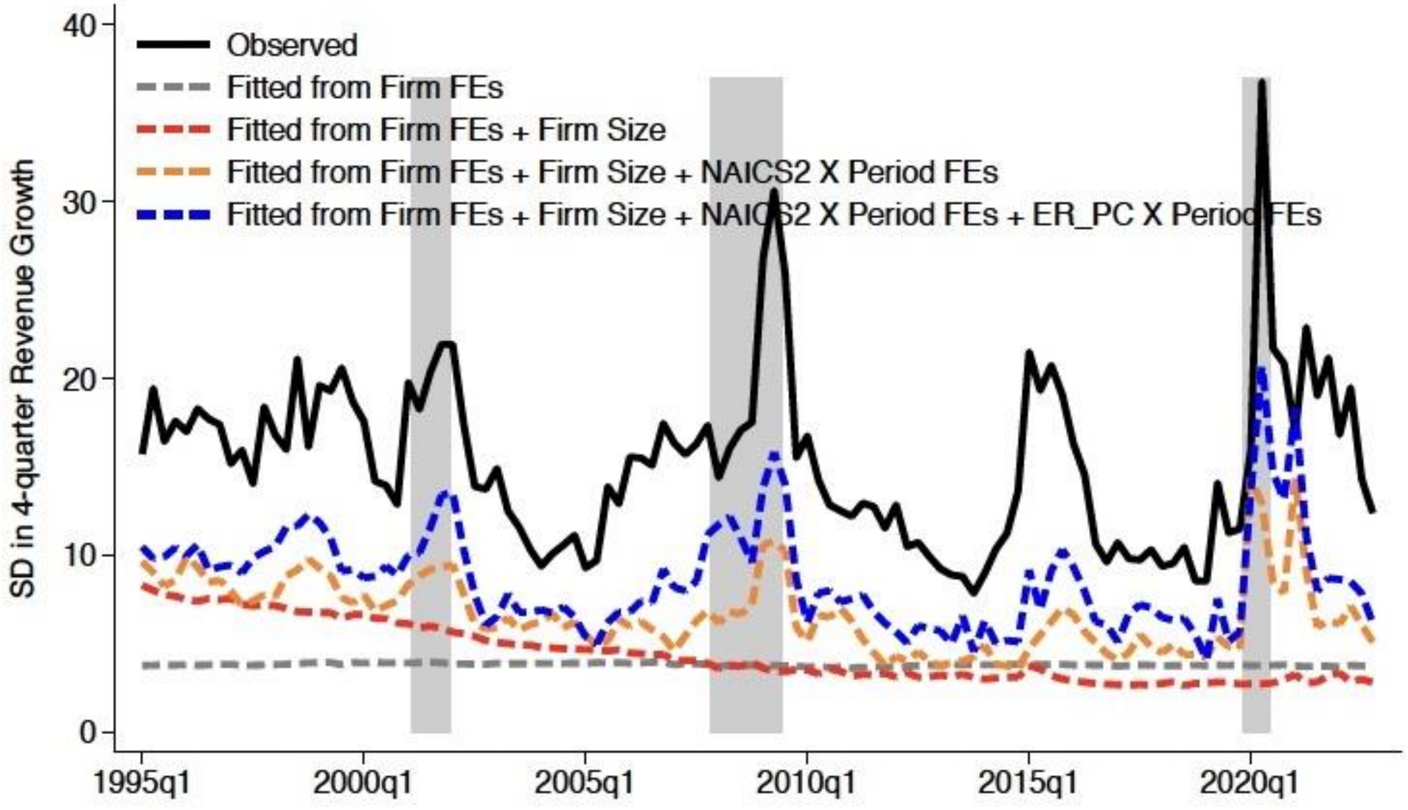


Figure 8: Dispersion in Firm-Level Revenue Growth since 1995

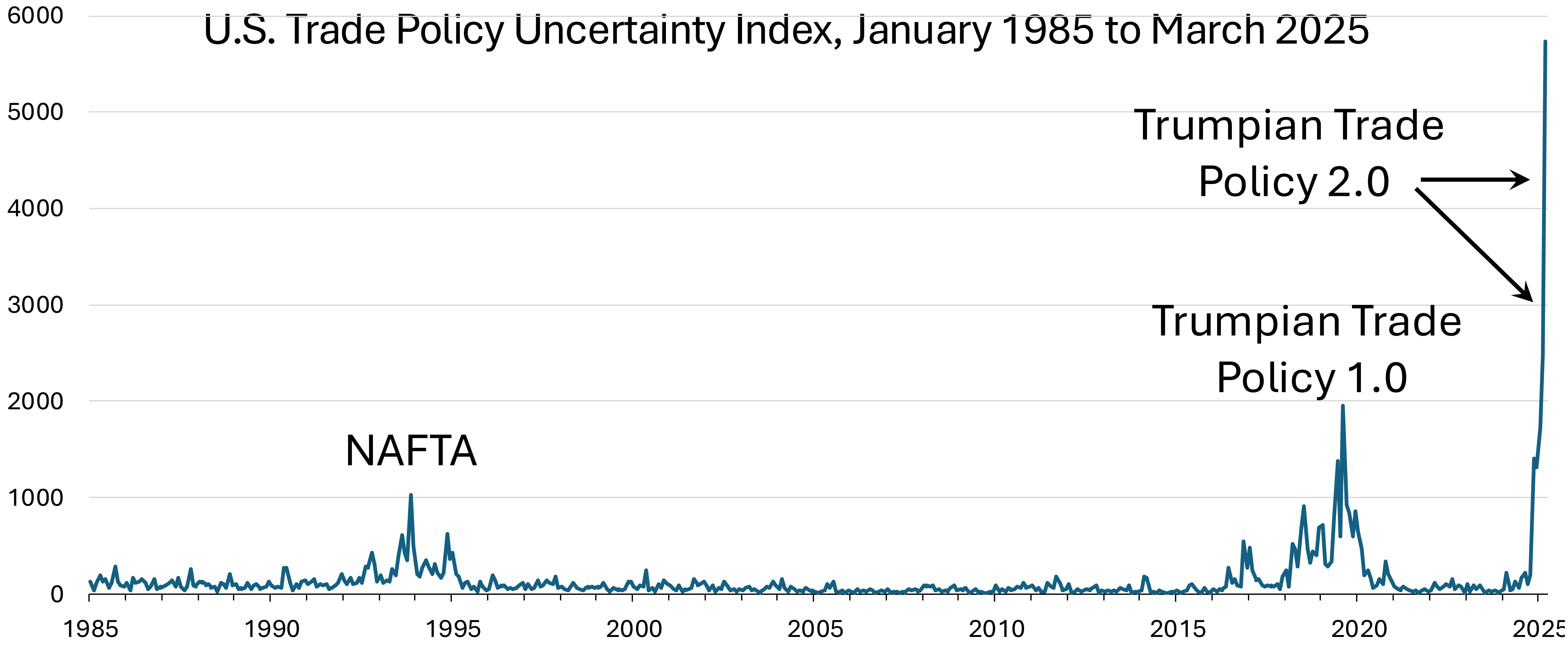
We define four-quarter revenue growth to be $\log(\text{rev}_{i,t}) - \log(\text{rev}_{i,t-4})$ and compute this value for a balanced sample of 950 firms from 1995Q1 through 2022Q4. The black curve plots the standard deviation in this variable by quarter, weighted by firm revenue in period $t-4$. The rest of the curves plot the weighted standard deviation in fitted values from alternative panel regression models that introduce variable in succession. The first model uses only firm fixed effects. The second model introduces firm size as measured by log assets interacted with quarter fixed effects. The third model introduces sector by quarter dummy variables. The fourth introduces the first 10 principal components of jump-date returns over the sample period.

Summary of Key Findings

1. The 2020-2022 period exhibits a huge flow of macro shocks that drove enormous dispersion across firms in abnormal returns and revenue growth.
2. Our text-based shock exposure measures (based on pre-pandemic regulatory filings) greatly improve on standard models in explaining the huge dispersion across firms in abnormal returns on jump days from 2020 to 2022.
3. Our shock exposure measures also explain most of the tremendous heterogeneity in firm-level revenue growth after the pandemic hits.
4. More broadly, countercyclical dispersion in firm-level growth rates arises from differences in firm-level exposures to macro shocks.

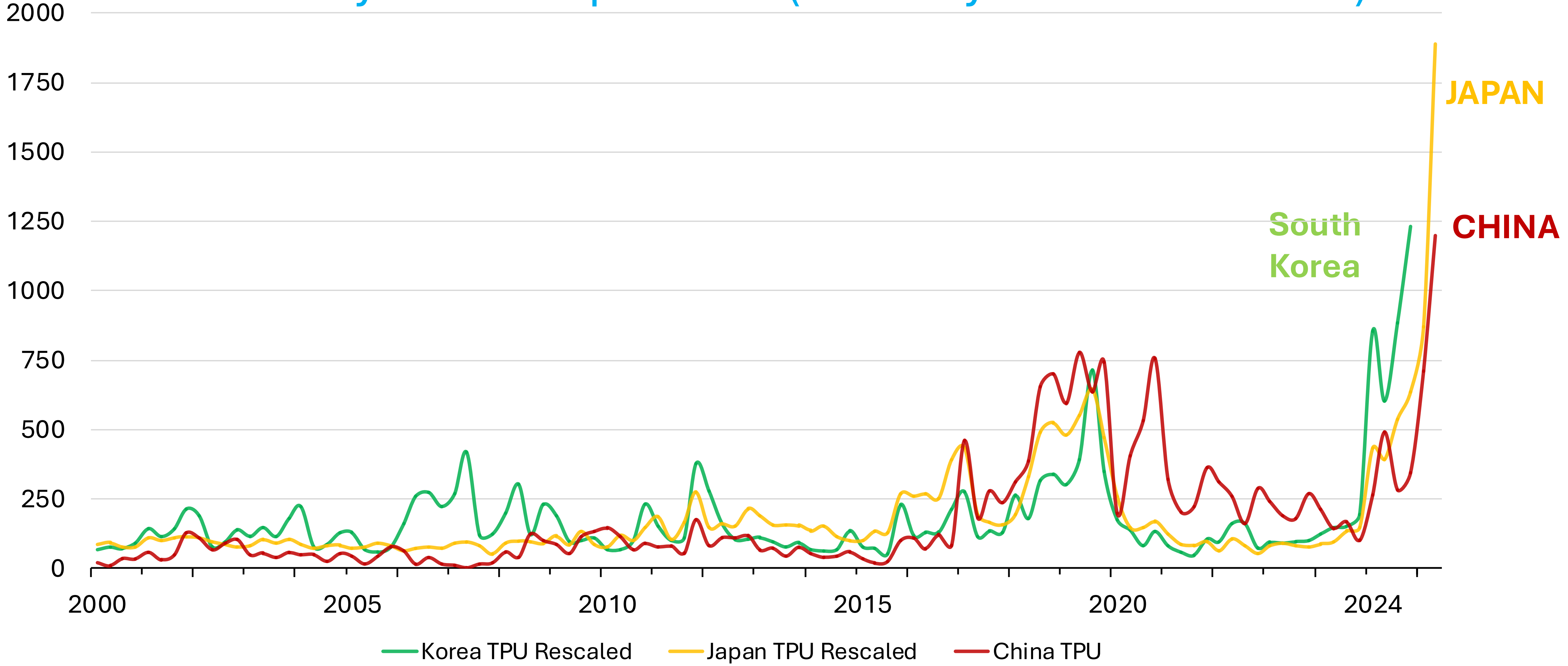
Destructive Trade Policy

U.S. Trade Policy Uncertainty Hit Unprecedented Levels Even Before "Liberation" Day



Source: Baker, Bloom and Davis (2016), as updated at www.PolicyUncertainty.com

Trade Policy Uncertainty Indexes for Three U.S. Trading Partners
January 2000 to April 2025 (February 2025 for S. Korea)



Source: Arbatli et al. (2023) for Japan; Davis, Liu and Sheng (2019) for China; and Cho and Kim (2023) for South Korea; as updated as updated at www.PolicyUncertainty.com. The monthly series for Japan and South Korea are rescaled to match the mean value for the China TPU series from January 2000 to December 2022. The chart shows quarterly averages from 2000 Q1 to Q3 2024 and monthly values thereafter through March 2025 (February 2025 for South Korea).

Trade Policy Shocks & Extreme Stock Market Moves

1900 to 2023: U.S. stock market moved > |2.5%| on 1,193 trading days, close to close.

- That's 3.5% of all trading days.

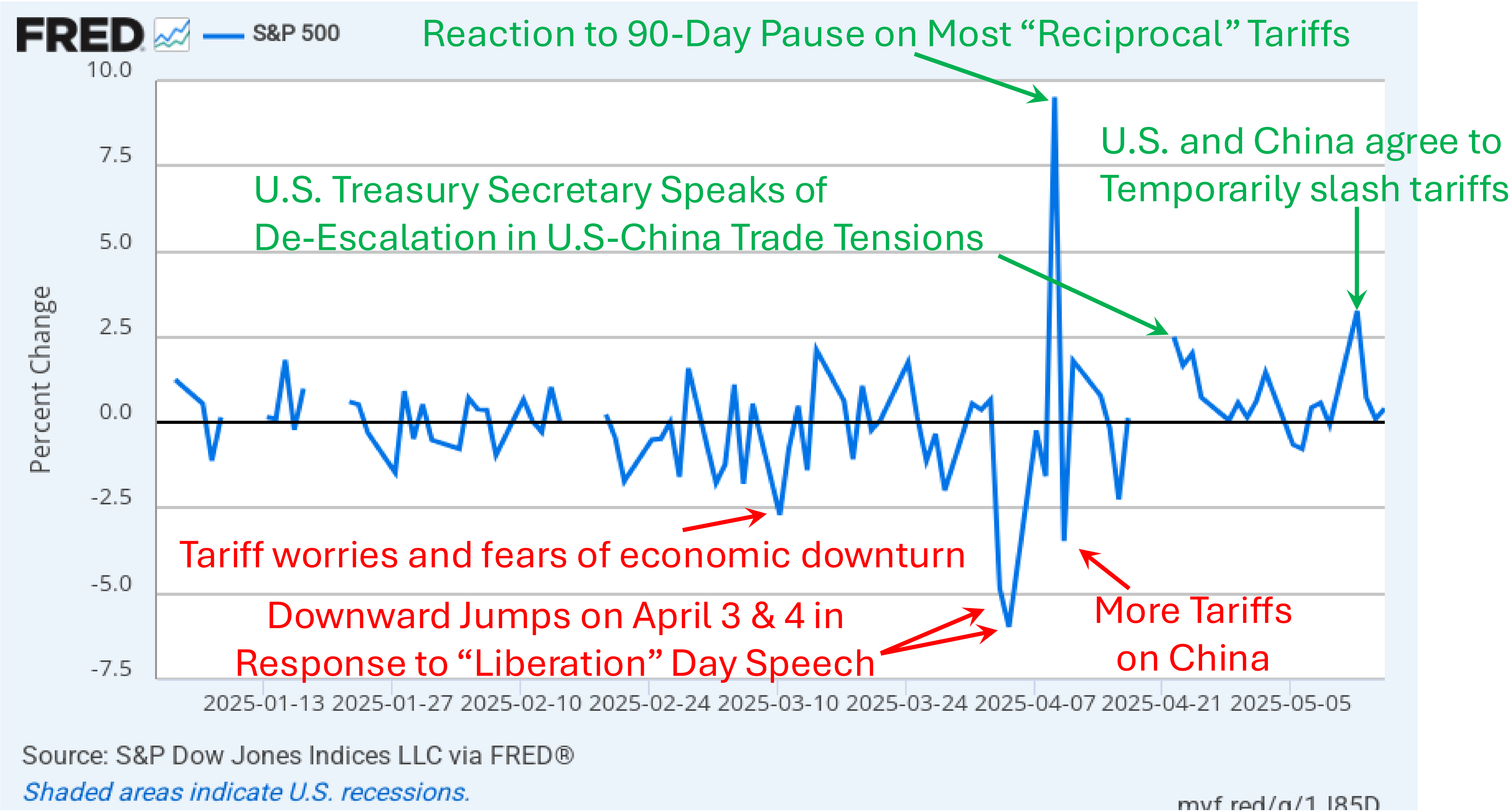
Next-day newspaper accounts attribute **ten** of these daily jumps to trade policy news (Baker et al., 2025b).

- Half occurred in 2018 and 2019.

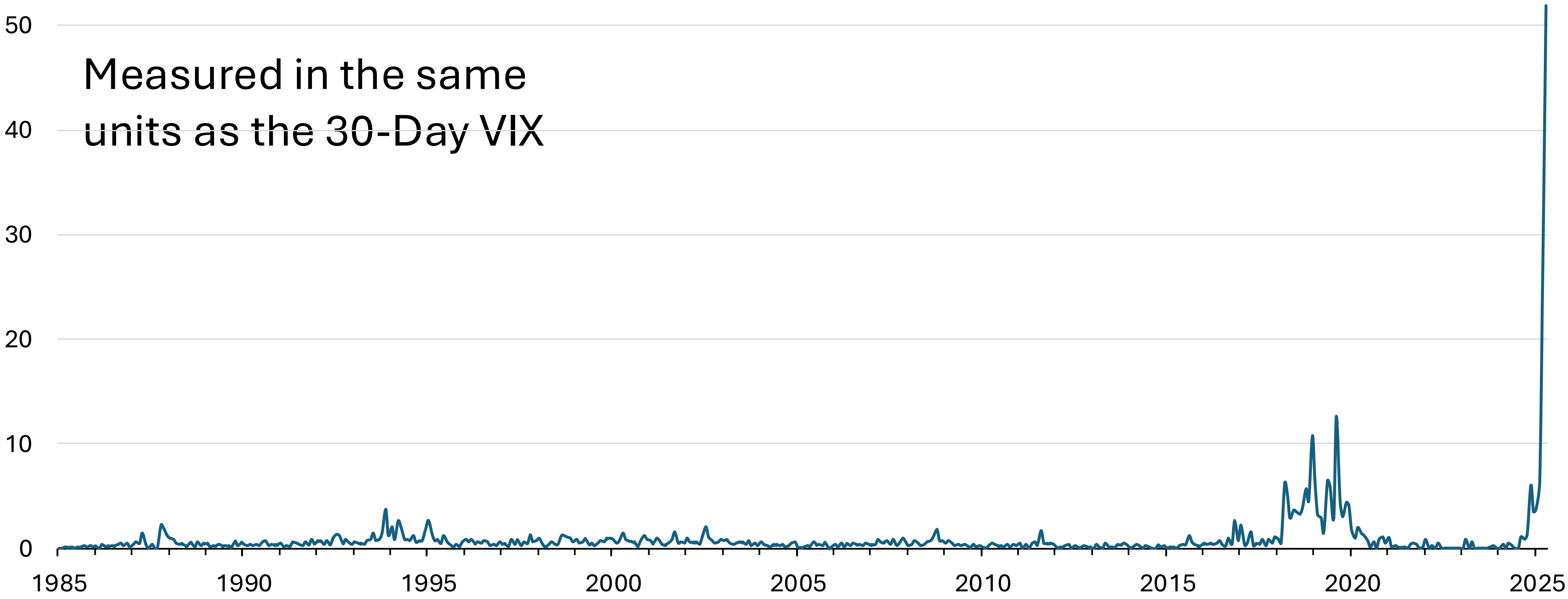
12 March 2025 (first new Trump tariffs) to 12 May 2025:

- Seven jumps triggered mostly or entirely by trade policy news

Daily Percent Change in S&P 500, 3 January to 15 May 2025

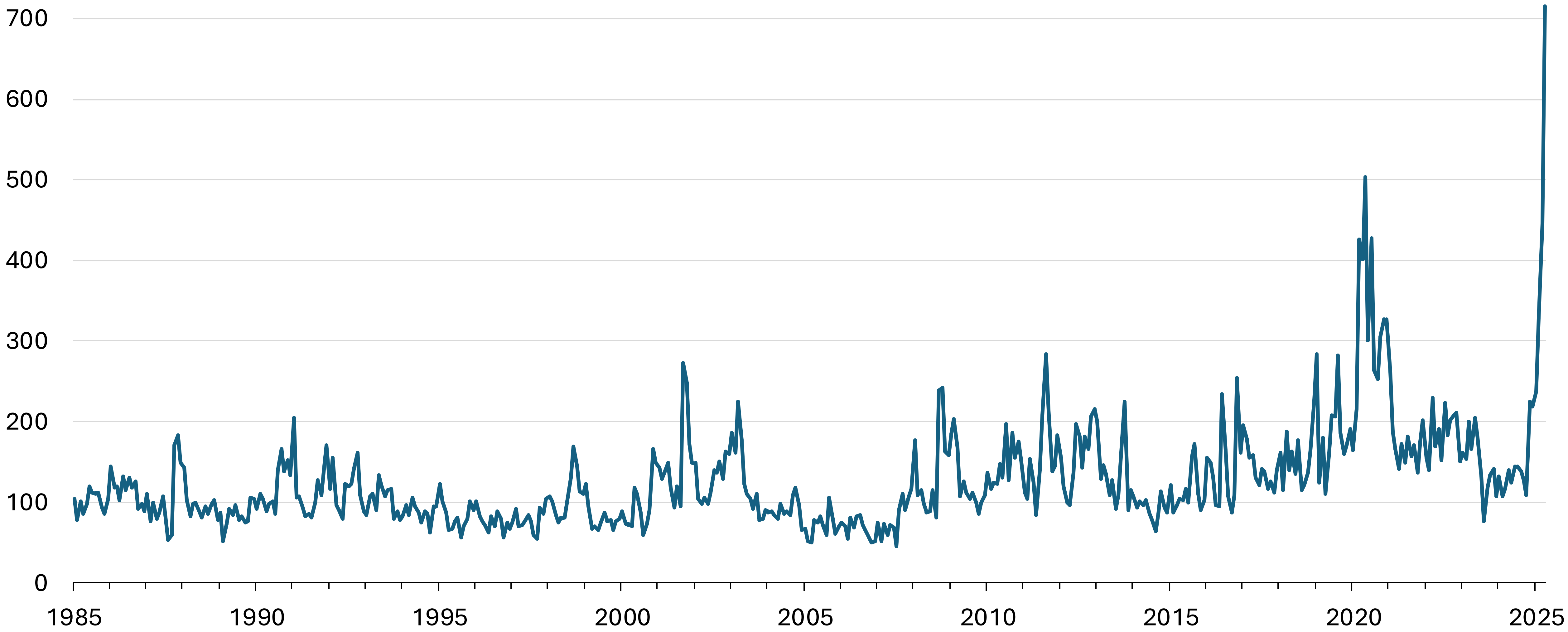


U.S. Equity Market Volatility Tracker for Trade Policy, January 1985 to April 2025



Source: Baker, Bloom, Davis and Kost (2025), as updated at www.PolicyUncertainty.com.

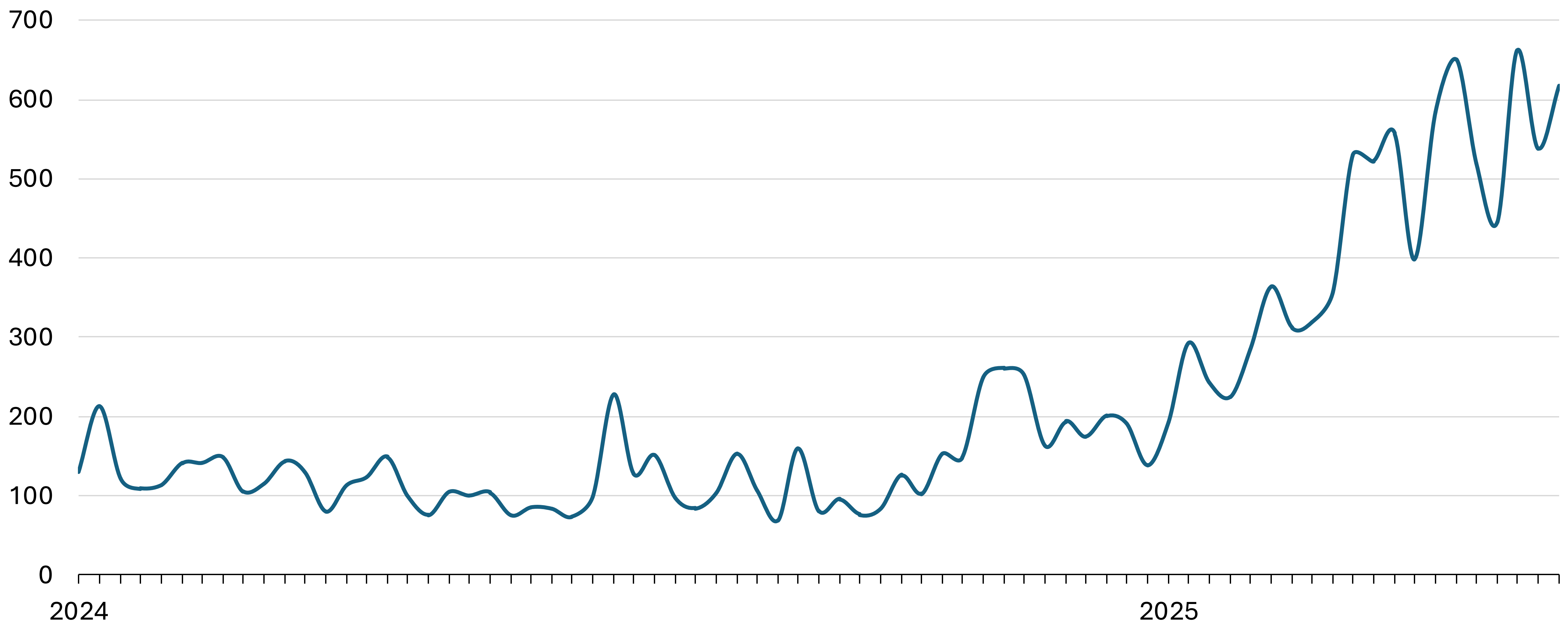
U.S. Economic Policy Uncertainty Index, January 1985 to April 2025



Note: The US EPU index reflects scaled monthly counts of articles from 10 major US newspapers that contain at least one word from three term sets: economic/economy (E), uncertain/uncertainty (U), and policy-related terms (P) such as legislation, deficit, regulation, Congress, Federal Reserve, White House. The series is normalized a mean value of 100 from 1985 to 2010.

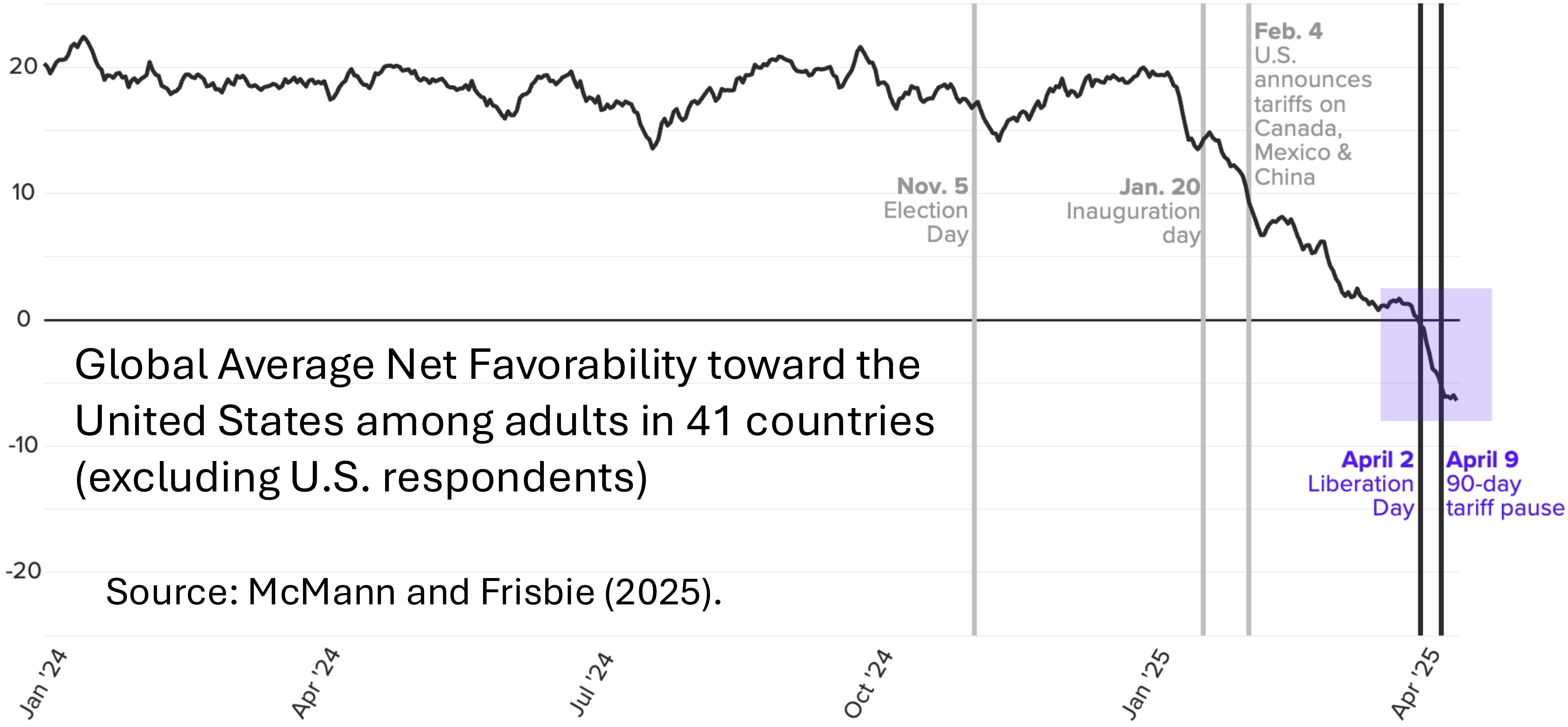
Source: "Measuring Economic Policy Uncertainty," by Scott R. Baker, Nick Bloom and Steven J. Davis (*Quarterly Journal of Economics*, 2016), as updated at https://www.policyuncertainty.com.

U.S. EPU Index, First Week of January 2024 to Week of May 11-17, 2025



Note: The US EPU index is calculated as weekly average of daily EPU index from over 2000 US newspaper archives in Access World News database. The daily EPU index reflects scaled daily counts of articles that contain at least one word from three term sets: economic/economy (E), uncertain/uncertainty (U), and policy-related terms (P) such as legislation, deficit, regulation, Congress, Federal Reserve, White House.
Source: "Measuring Economic Policy Uncertainty" by Scott R. Baker, Nick Bloom and Steven J. Davis (*Quarterly Journal of Economics*, 2016), as updated at https://policyuncertainty.com.

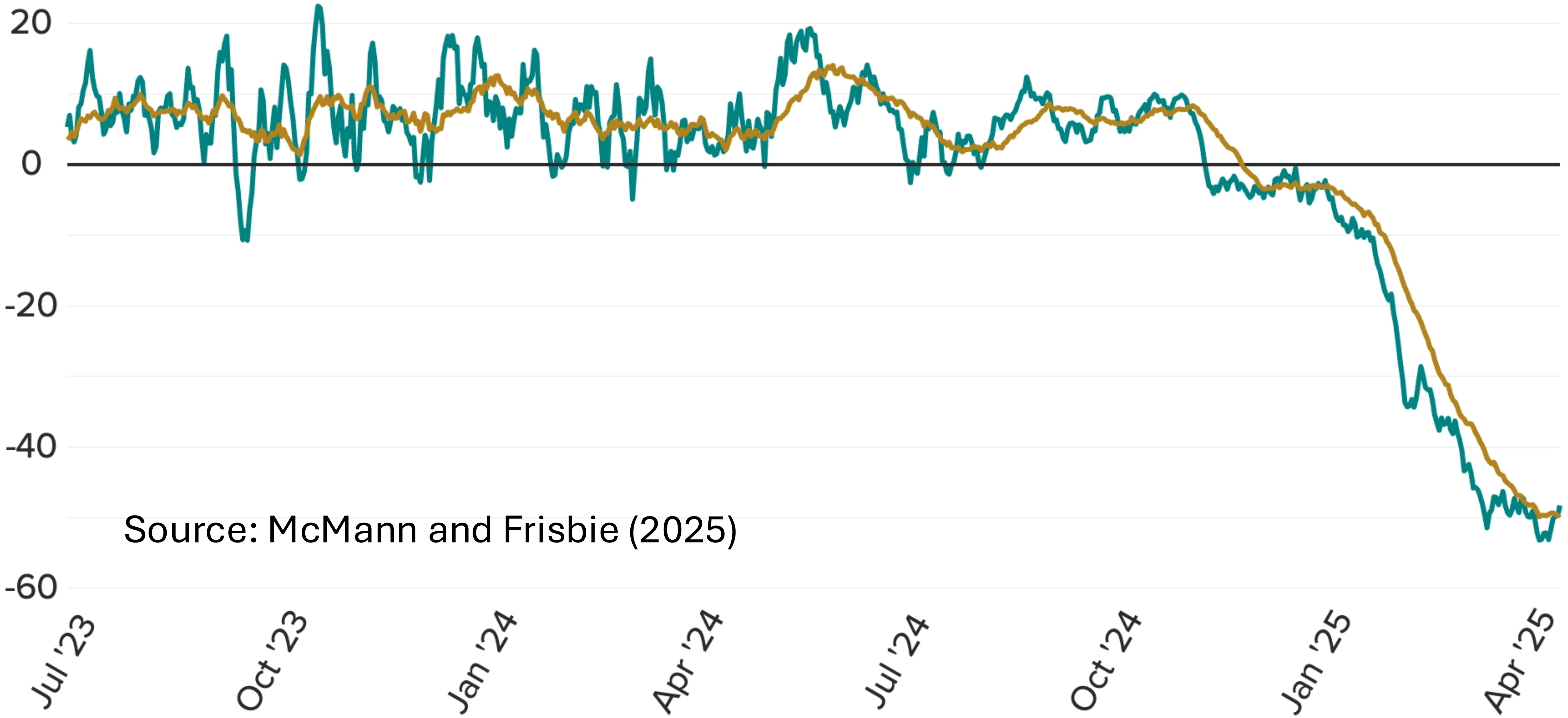
Losing Friends



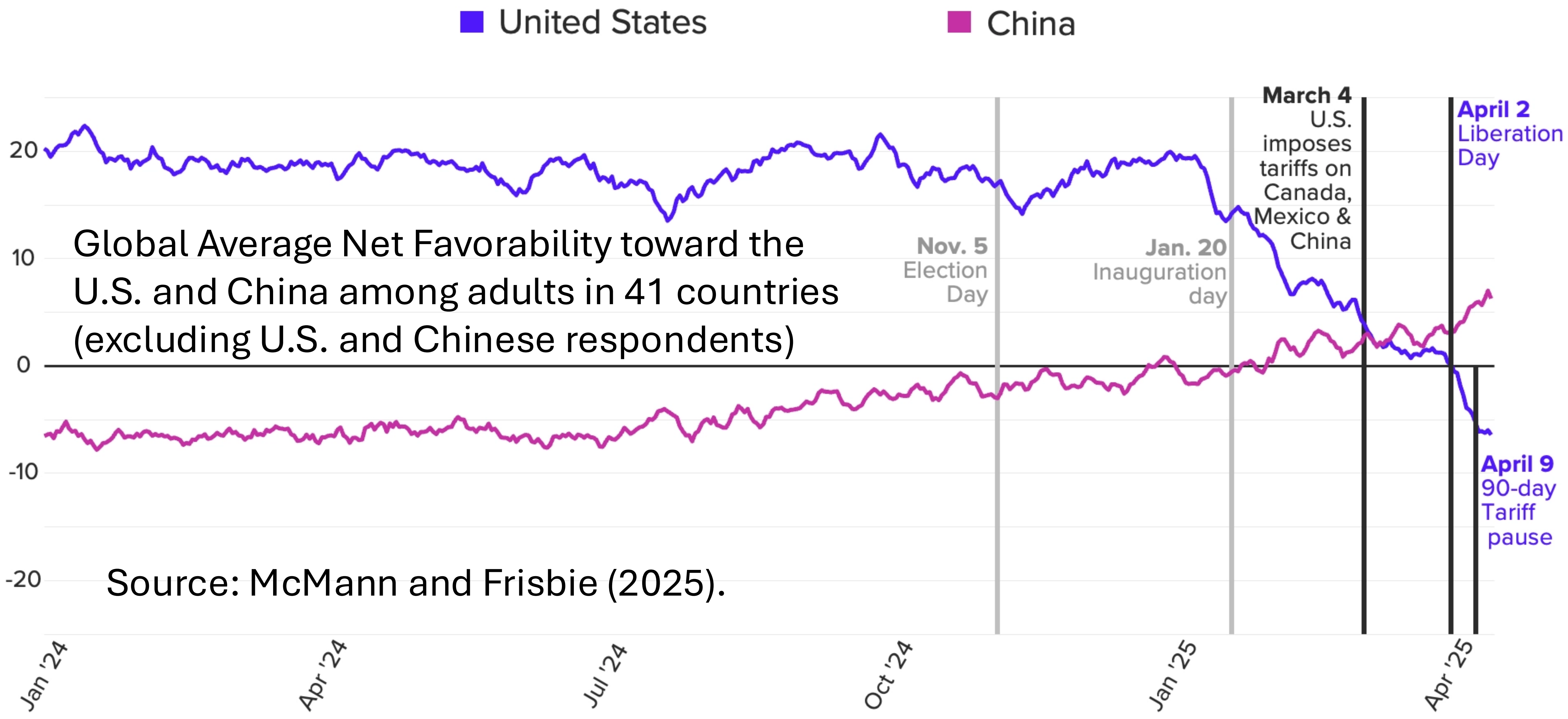
Global Average Net Favorability toward the United States among adults in 41 countries (excluding U.S. respondents)

Source: McMann and Frisbie (2025).

Canada, Net Favorability toward the U.S.



Creating Openings for Adversaries

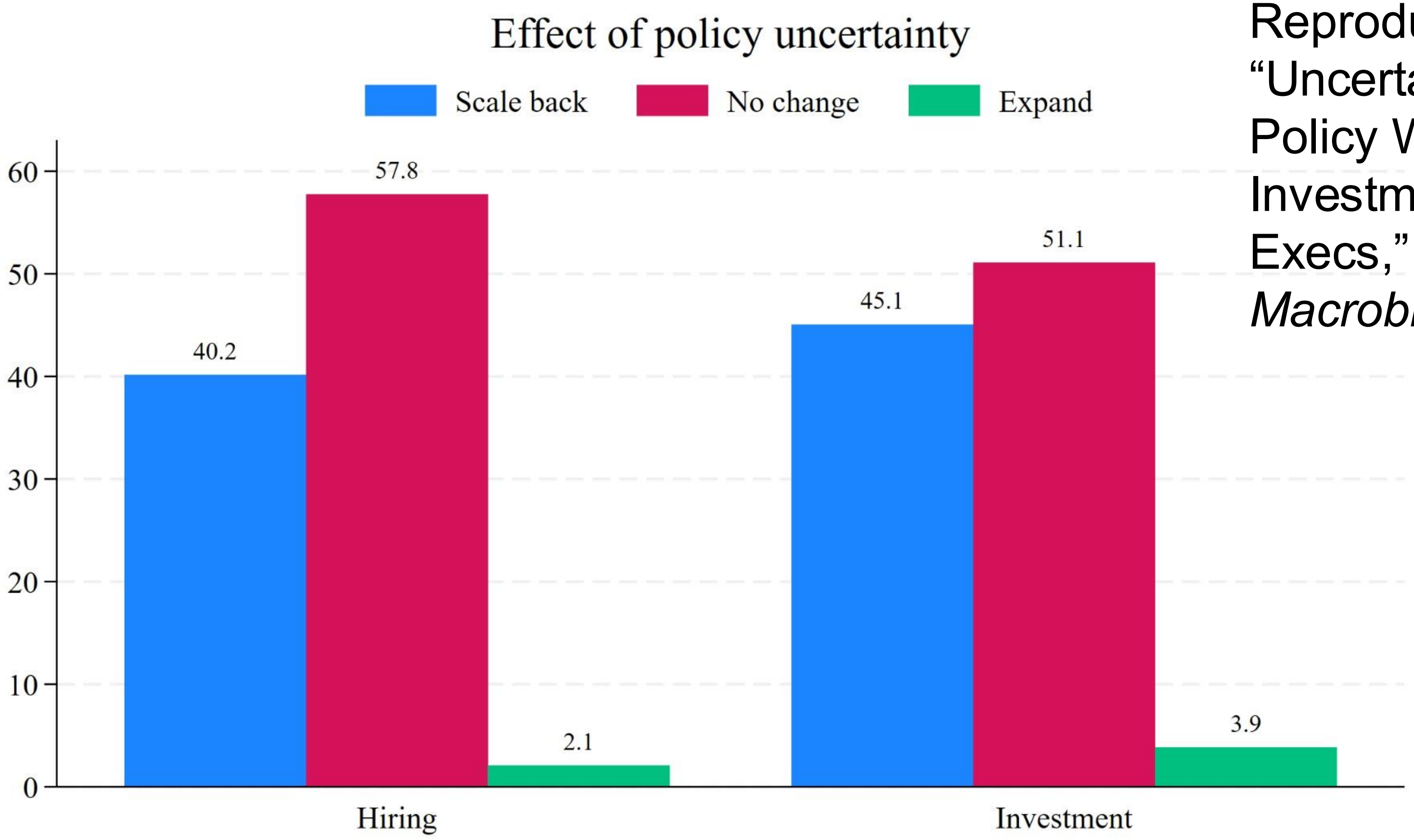


Global Average Net Favorability toward the U.S. and China among adults in 41 countries (excluding U.S. and Chinese respondents)

Source: McMann and Frisbie (2025).

Over 40% of business executives say they plan to scale back hiring in their firms in the next 6 months due to policy uncertainty. 45% say they will scale back investment for the same reason.

Question: How has uncertainty about tariffs, taxes, government spending, monetary policy, or regulation affected your firm's plans for hiring/investment over the next 6 months?

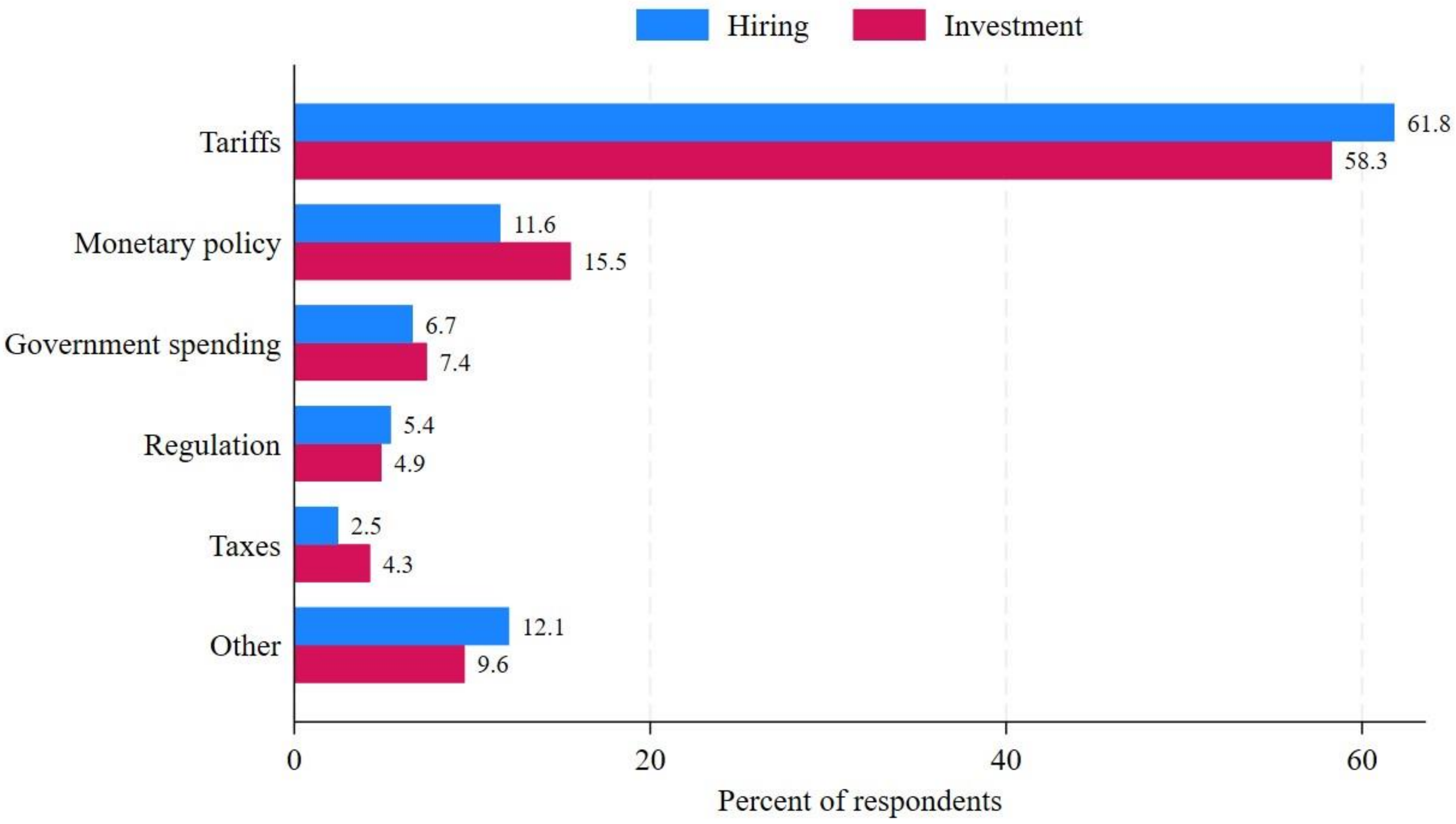


Reproduced from "Uncertainty over (Trade) Policy Will Cut Hiring and Investment, Say Business Execs," Atlanta Fed *Macroblog*, 15 May 2025.

Note: These questions were fielded in the April 2025 SBU survey wave (4/14/25 – 4/25/25). Data sampled across all states and private sectors. Data winsorized at the 1st and 99th percentiles. N=961.

Tariffs are the top source of uncertainty leading firms to scale back investment and hiring plans for the next 6 months.

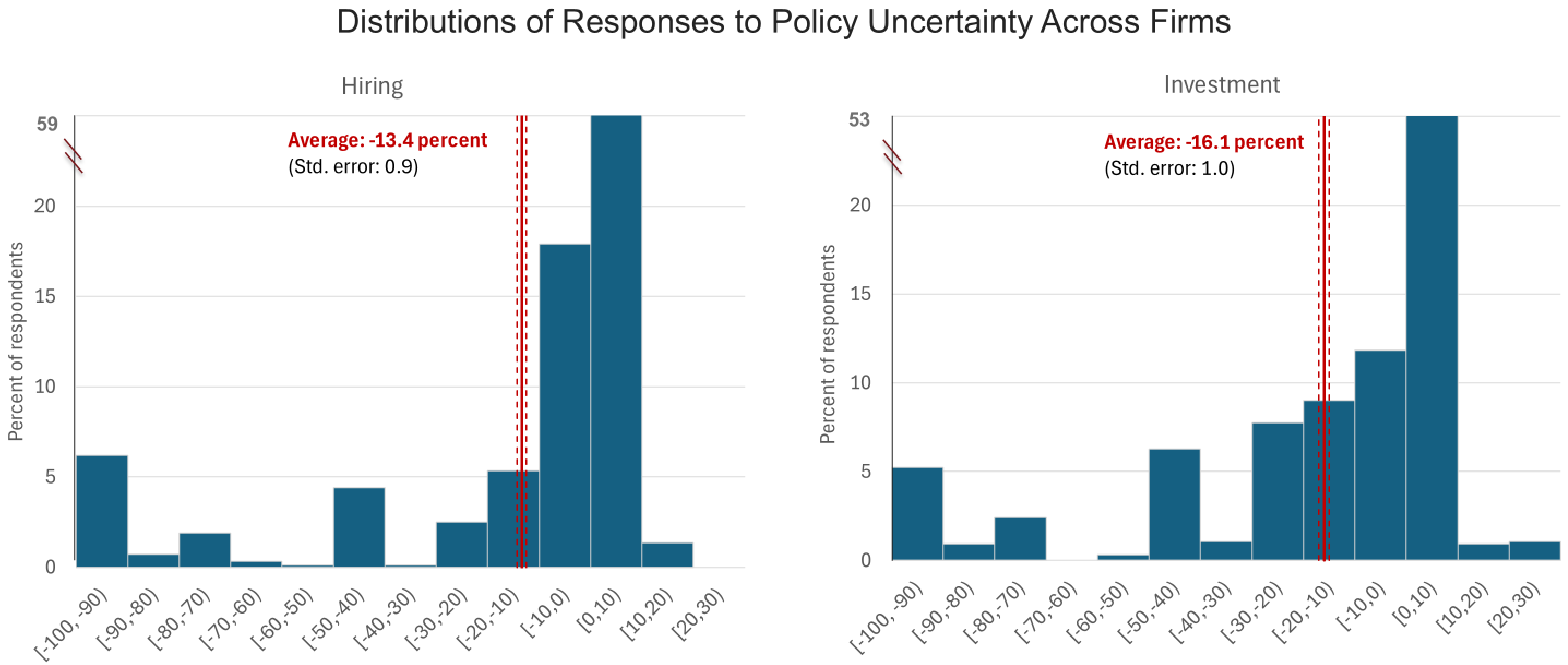
Question: What is your firm's top concern with respect to uncertainty affecting your firm's hiring/investment plans over the next 6 months?



Note: These questions were fielded in the April 2025 SBU survey wave (4/14/25 – 4/25/25). Data sampled across all states and private sectors. Data winsorized at the 1st and 99th percentiles. N_{hire}=406, N_{invest}=470.

Policy uncertainty is causing firms to pull back on near-term hiring and investment by 13.4 percent and 16.1 percent, respectively.

Question: By what percentage do you expect to scale back/expand hiring over the next 6 months due to uncertainty?



Note: These questions were fielded in the April 2025 SBU survey wave (4/14/25 – 4/25/25). Data sampled across all states and private sectors. Data winsorized at the 1st and 99th percentiles. N=955. Red line and dashed region represent the sample mean and standard error, respectively.

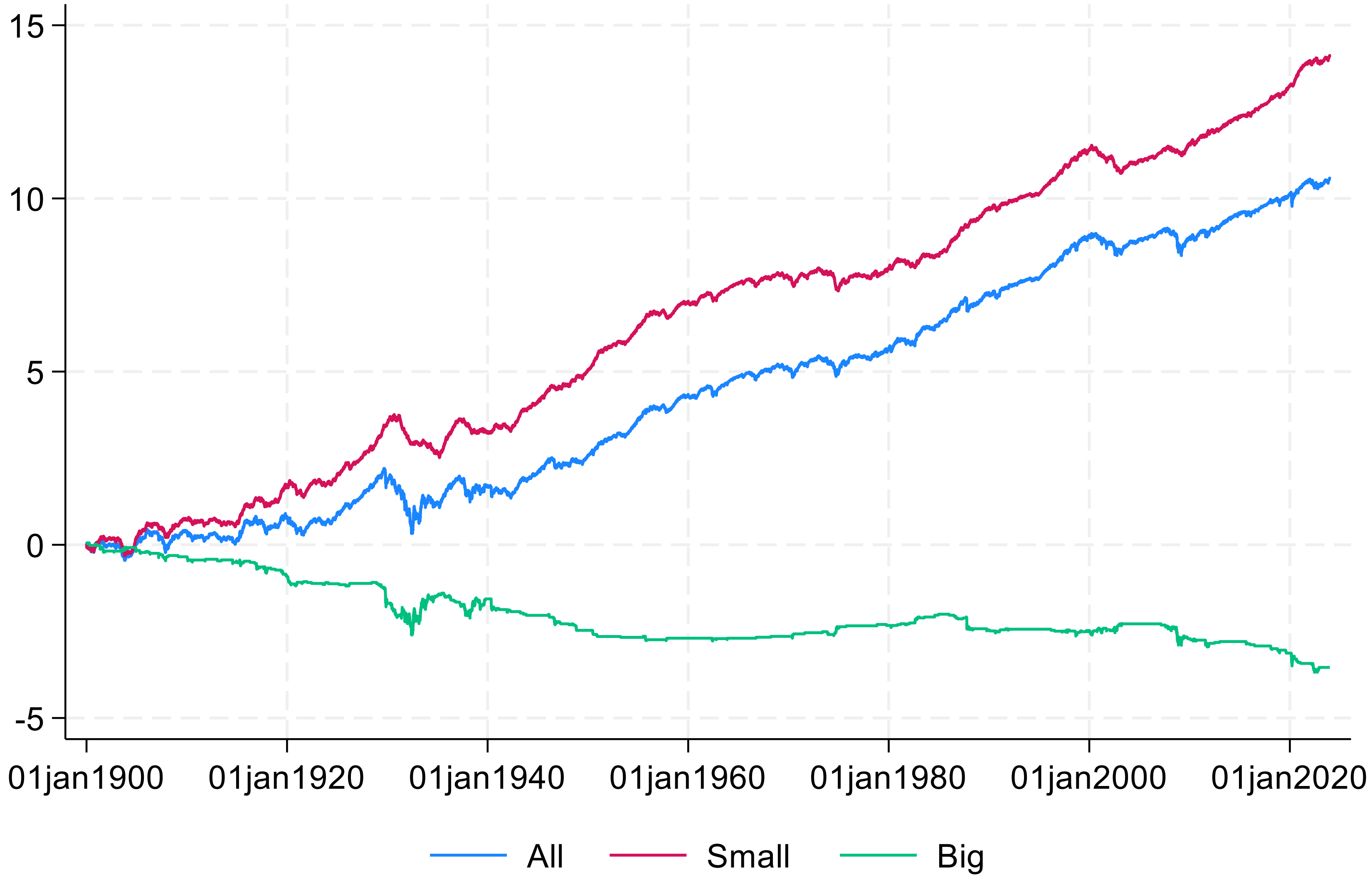
Shredding Past Trade Agreements, Devaluing Future Ones

[Trump's] tariffs blow an enormous hole in the liberal trade order that America has led and fostered since the second world war. They undermine every free-trade agreement America has ever signed. … If Mr Trump is willing to rip up his own agreement—known as the USMCA —with [Canada and Mexico] then all past agreements are null and void, and future ones are of limited value. No one can sign any such deal with confidence if tariffs can be imposed on a whim.

Douglas Irwin, *The Economist*, 3 April 2025

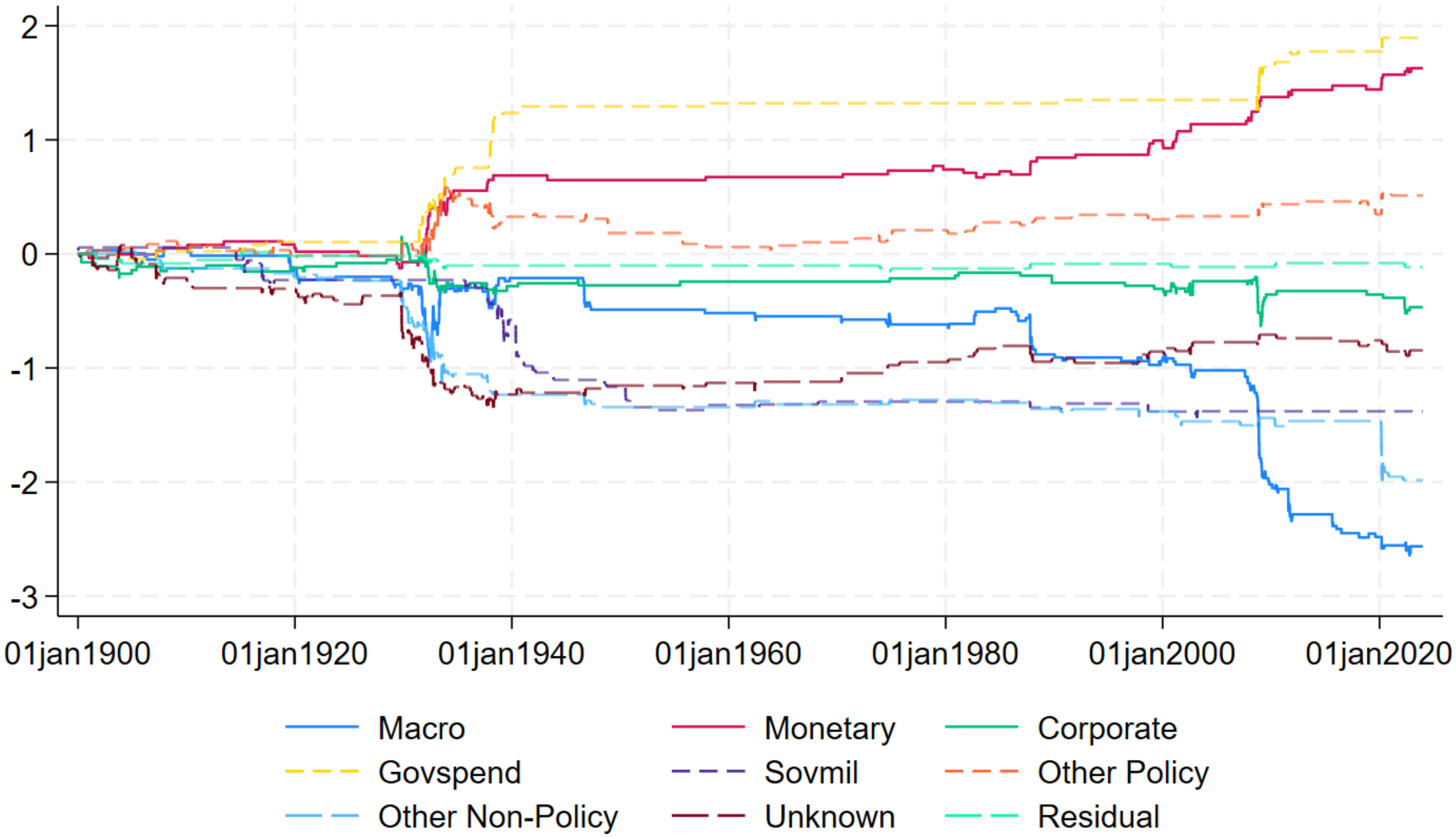
Extra Slides
For “Jumps”

Figure A3: Cumulative U.S. Equity Returns, 1900 to 2023
Panel A: Breakdown between Jump Days and Other Days



Notes: The blue curve shows the cumulative sum of daily log returns on the U.S. stock market from 2 January 1900 to 29 December 2023. The red curve shows the same measure restricted to trading days with "Small" moves (< |2.5%|), and the green curve shows the same measure restricted to jump days.

Figure A3, Cumulative U.S. Equity Returns, 1900 to 2023
Panel B: Breakdown by Jump Category



Notes: This chart plots the cumulative sum of daily log returns on the U.S. stock market from 2 January 1900 to 29 December 2023 for the indicated jump categories. The "Residual" plot covers all categories that are not listed explicitly.

Table 2: Pairwise Agreement Rates for Human Classifications of the Primary Jump Reason

Time Period	1900-1979		1980-2023	
	Policy vs. Non-Policy	Granular Categories	Policy vs. Non-Policy	Granular Categories
Within WSJ	91.9%	76.6%	92.6%	78.0%
All Coders Within Paper	89.5%	71.3%	90.3%	74.2%
All Coders & All Papers	76.4%	45.9%	81.0%	58.2%
With Random Assignment	52.8%	12.6%	58.1%	18.6%
Standard Error	1.5%	1.8%	2.1%	2.6%

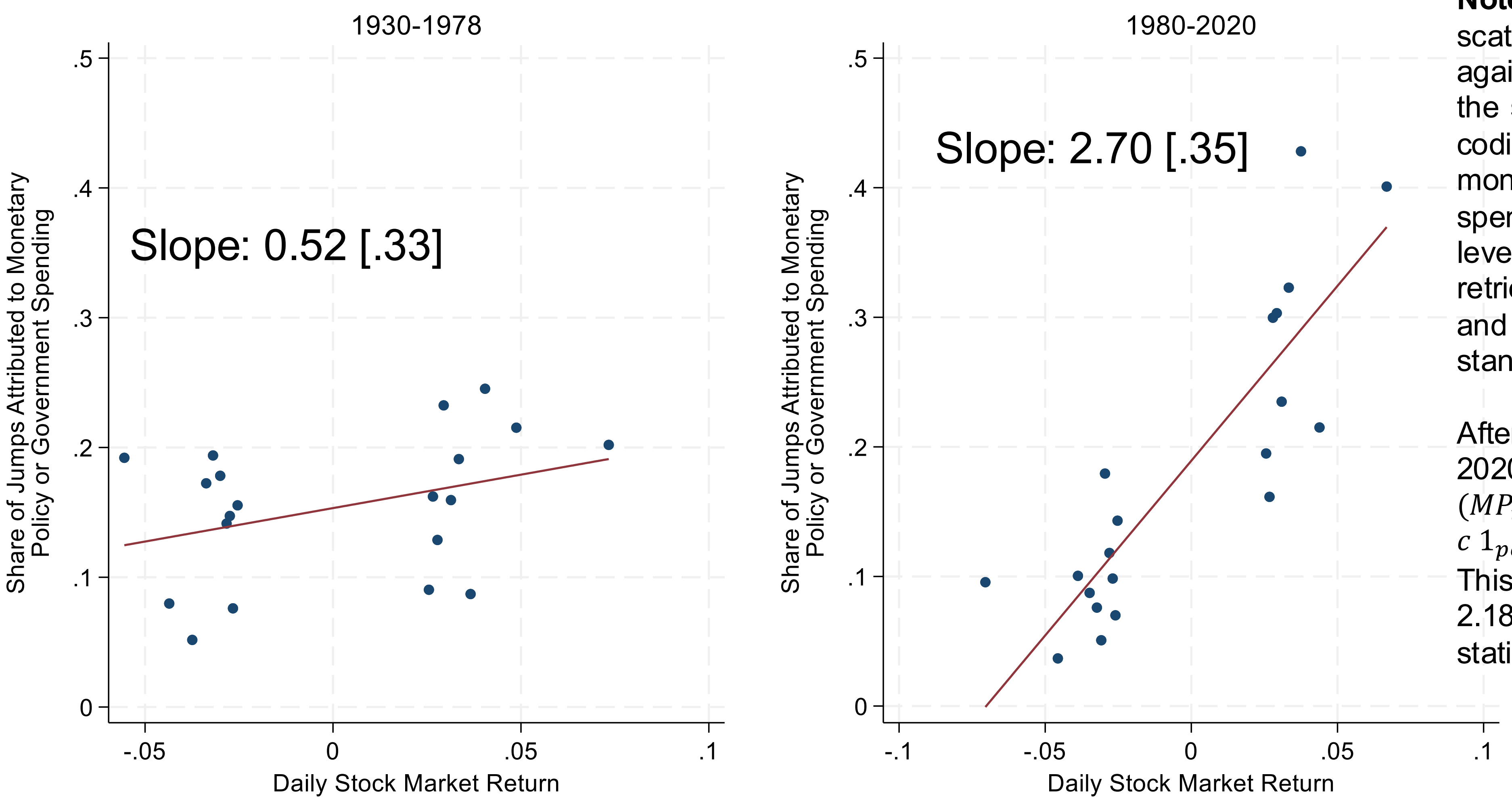
Notes: There are 6,684 codings of 802 U.S. jumps from 1900-1979 and 3,715 codings of 377 U.S. jumps from 1980-2023. "Granular" refers to the 16 jump categories listed in Table 1 (excluding "No Article Found"). "Policy" encompasses Monetary Policy, Government Spending, Sovereign Military, Other Policy, Regulation, Trade Policy, Exchange Rate Policy, Elections, and Taxes. "Non-Policy" covers all other categories. "All Papers" encompass the *Wall Street Journal, New York Times, Chicago Tribune, Washington Post*, and *Los Angeles Times*. We compute outcomes implied by "Random Assignment" using the unconditional jump distribution for the indicated period and breakdown, as reported in Table 1. To compute standard errors, we use the normal approximation for the standard error of a binomial random variable: $\sqrt{p(1-p)/n}$, where p is the probability of agreement under random assignment and n is the number of jumps in the indicated period. This formula yields a conservative estimate for the standard error, because we have multiple pairwise comparisons for each of the n jumps.

Table 3: Validation Checks on the Categorization of U.S. Stock Market Jumps

	Monetary 1994-2023	Macro 1953-2023	Elections 1900-2023	Monetary 1994-2023	Macro 1953-2023	Elections 1900-2023
FOMC meeting at t or t-1	3.48***			3.35***		
	(0.361)			(0.367)		
Macro Announcement at t	-0.08	0.56***		0.03	0.91***	
	(0.149)	(0.137)		(0.225)	(0.176)	
Election at t or t-1	-0.6	0.59	4.67***	-0.74	0.58	4.67***
	(1.068)	(0.952)	(0.220)	(1.071)	(0.953)	(0.220)
Observations	7,552	17,872	33,540	7,552	17,872	33,540
R-Squared	0.012	0.001	0.013	0.013	0.002	0.013
# Codings in Category	36	145	28	36	145	28
Day of Week FE	No	No	No	Yes	Yes	Yes

Notes: Each column reports a regression of jump coding values (times 100 for scaling purposes) for the indicated category on a set of known information-release dates. For FOMC meetings, we consider jumps that occur on the last day of, or the day after the meeting. For elections, because the results are not usually known by the end of the trading day, we consider the day after Federal elections as well. Because Macro Announcements usually occur before the markets open, we only count the day of the announcement. Macro Announcements cover news releases for the CPI, jobless claims, and the Employment Situation Report. Date range varies by column. *** p<0.01, ** p<0.05, * p<0.1. US data, date range varies by column.

Figure A7: Monetary Policy and Government Spending News Triggers a Larger Share of Positive than Negative Jumps, Especially After 1980, in U.K. Data from 1930 to 2020



Notes: Each panel shows a bin scatter (n=20) of jump-level scores against jump-day stock returns, where the score is the fraction of the jump's codings attributed to news about monetary policy or government spending. We also regress the jump-level scores on jump-day returns, retrieve and plot the slope estimate, and report the slope coefficient and standard error in the body of the chart.

After pooling the data from 1930 to 2020, we run the following regression, $(MP_t + \mathrm{GS_t}) = a + b\, return_t + c\, 1_{post80} + d\, return_t \times 1_{post80} + e_{\mathrm{t}}$. This regression yields a coefficient of 2.18 on the interaction term with a t-statistic of 4.47.

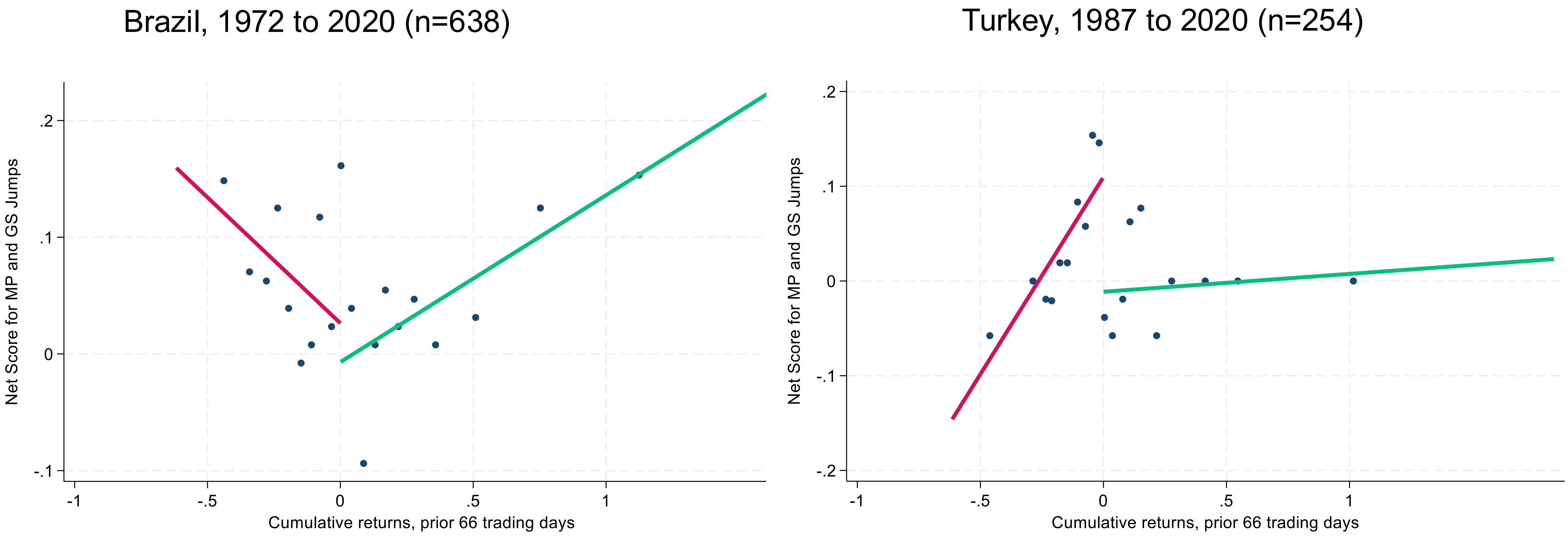
Table 4: The Put-Like Character of Jumps Triggered by MP and GS, All Countries Except Brazil and Turkey

Dependent variable: $NET(MP_t + GS_{\mathrm{t}})$

B. 17-Country Sample, 1980 to 2020	Gov. Spend + Monetary		Government Spending		Monetary Policy	
	Jump Days	All Days	Jump Days	All Days	Jump Days	All Days
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Return Past 66 Trading Days * 1[Negative Return]	-0.418***	-0.139***	-0.292***	-0.078***	-0.126***	-0.061***
	(0.063)	(0.011)	(0.048)	(0.009)	(0.042)	(0.006)
Cumulative Return Past 66 Trading Days * 1[Positive Return]	-0.017	0.000	0.014	0.001	-0.031	-0.001
	(0.055)	(0.003)	(0.027)	(0.001)	(0.046)	(0.002)
1[Positive Return]	-0.016	0.005***	0.004	0.003***	-0.020	0.002***
	(0.016)	(0.001)	(0.010)	(0.001)	(0.013)	0.000
Intercept	0.024**	-0.005***	(0.004)	-0.003***	0.027***	-0.001***
	(0.011)	(0.001)	(0.008)	(0.001)	(0.008)	0.000
Observations	5,324	136,524	5,324	136,524	5,324	136,524
R-squared	0.02	0.01	0.016	0.007	0.007	0.004

100

Figure A8: Low Stock Returns over the Preceding 66 Trading Days Do Not Foreshadow Upward Jumps Attributed to Monetary Policy and Government Spending in Brazil or Turkey



Notes: These charts show bin scatters of jump-level $NET(MP_t + GS_t)$ values on own-country market returns over the prior 66 trading days in Brazil and Turkey. $NET(MP_t + GS_t)$ equals the share of codings attributed to monetary policy or government spending for upward jumps and (-1) times that share for downward jumps. As noted in the text, we code only a randomly selected subset of jumps in each country. We exclude jumps for which we could not locate a next-day newspaper article.

What Makes Turkey Distinctive?

Newspaper accounts attribute an unusually large share of jumps in the Turkish stock market to “Elections and Political Transitions” and “Sovereign Military & Security Actions.” *Jumps in these categories do <u>not</u> exhibit a positive tilt, unlike those attributed to “Monetary Policy & Central Banking” and “Government Spending.”* Turkey is also known for the non-technocratic conduct of monetary policy.

Percent of All Jumps in Selected Categories, 1980 to 2020

	Turkey	United States	17 Other Countries
Sovereign Military & Security Actions	12.6%	3.2%	3.4%
Elections & Political Transitions	8.6%	1.6%	3.1%

Table A5: The Put-Like Character of Monetary Policy and Government Spending Reactions to Stock Market Movements Has Strengthened Over Time.

Dependent variable: Share of codings attributed to indicated categories for upward jumps and (-1) times that share for downward jumps.

	US 1900-2023 (1)	UK 1930-2020 (2)	US 1980-2023 (3)	UK 1980-2020 (4)
Cumulative Return Past 66 Trading Days * 1[Negative Return]	-0.142***	-0.093***	-0.293***	-0.226***
	(0.025)	(0.024)	(0.076)	(0.055)
Cumulative Return Past 66 Trading Days * 1[Positive Return]	-0.001	0.040**	-0.020	-0.007
	(0.013)	(0.019)	(0.012)	(0.008)
1[Positive Return]	0.004**	0.001	0.009**	0.007**
	(0.002)	(0.002)	(0.004)	(0.003)
Intercept	-0.004***	-0.003**	-0.008**	-0.006**
	(0.001)	(0.001)	(0.004)	(0.003)
Observations	33,474	22,913	11,094	10,201
R-squared	0.01	0.007	0.021	0.02

Notes: We regress $NET(MP_t + GS_t)$ values on own-country market returns over the prior 66 trading days. The frequency of U.S. jumps is 3.515 percent of all trading days from 1900 to 2023 and 0.498 percent for jumps attributed to monetary policy or government spending. The mean value of $NET(MP_t + GS_t)$ is 0.200 percent. The frequency of jumps in the 17-country sample is 3.752 percent of all trading days and 0.597 percent for jumps attributed to monetary policy or government spending. The mean value of $NET(MP_t + GS_t)$ is 0.217 percent.

Table 5: High Intra-Day Concentration of U.S. Stock Market Jumps Is Associated with Greater Clarity about the Jump Reason

	100 X Intra-Day Concentration of Market-Level Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Clarity Index	1.924***	1.65***				
	(0.579)	(0.596)				
Avg. Ease of Coding			0.22			
			(0.571)			
Avg. Confidence				1.59***		
				(0.569)		
Share Known					1.52**	
					(0.712)	
Pairwise Agreement						2.03***
						(0.464)
R-squared	0.037	0.077	0.052	0.075	0.067	0.106
Return & HAR Controls	NO	YES	YES	YES	YES	YES

Notes: The dependent variable is the intra-day concentration of market-level returns on jump days, in defined in Section 4.2. Each column corresponds to a separate regression of intra-day concentration on our Clarity Index or one of its components. The Clarity Index and each component has mean zero and unit standard deviation. The sample covers 350 US jumps from 1985 to 2023, the period for which we have high-frequency data on market-level returns from TickWrite for the S&P 500 Spot Market or CRSP US Intraday Second by Second data, 1985-2023. The sample mean value of intra-day concentration is 0.153, and its standard deviation is 0.059. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Clarity Fluctuations Are Positively Autocorrelated, US Data, 1900-2023

	Clarity of Jump at t x 100		
	(1)	(2)	(3)
Clarity of Last Jump x 100	0.367***	0.234***	0.219***
	(0.03)	(0.03)	(0.03)
Linear Time Trend		0.00409***	0.00468***
		(0.00)	(0.00)
Post War Dummy		-16.040	-27.16*
		(14.03)	(14.51)
Linear Time Trend x Post War Dummy		-0.00223**	-0.00251**
		(0.00)	(0.00)
Last Jump Return, Positive Segment			-284.50
			(176.40)
bsolute Value of Last Jump Return, Negative Segme			-615.1***
			(181.90)
Volatility, Prior Day			-1473.00
			(1937.00)
Volatility, Prior Week			-457.20
			(737.00)
Volatility, Prior Month			-215.30
			(235.40)
Observations	1,171	1,171	1,171
R-squared	0.134	0.218	0.234

Notes: "Last Jump" refers to the most recent jump before the one at *t*. Robust standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Comparison to the Cutler, Poterba and Summers Characterization of the 50 Largest Daily Moves in the S&P Stock Index from 1946 to 1987

	Primary Category Agreement	Primary or Secondary Category Agreement	Observations
High Clarity	79.7%	87.5%	32
Low Clarity	38.0%	45.4%	18
Total	64.7%	72.3%	50

Notes: Cutler, Poterba and Summers (CPS) attribute a “cause” to the 50 largest U.S. stock market jumps from 1946 to 1987 based on coverage in the New York Times. See their Table 4. For each jump, we map their description of the cause to a primary and, sometimes, a secondary category, using our classification scheme. We then compare the resulting CPS classification to our classification as follows: For any given coding of the jump in question, we set “Primary category agreement” to 1 if the CPS primary category matches ours, and 0 otherwise. We set “Primary or secondary category agreement” to 1 if there is overlap between the CPS primary and secondary categories and our primary and secondary categories, and 0 otherwise. We then average over all codings for the jump in question to obtain an average agreement rate (over codings) for a given jump. Lastly, we average over jumps to obtain the entries reported in the table. ”High” and “Low” clarity jumps have Clarity values greater or less than 0, respectively.

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	Number of Daily U.S. Stock Market Jumps Greater than |2.5%|	Number Attributed to Economic Fallout of Pandemics	Number Attributed to Policy Responses to Pandemics
2 January 1900 to 21 February 2020	1,116	0	0
24 February 2020 to 30 April 2020	27	13.4	10.4

Note: Tabulated from results in Baker, Bloom, Davis and Sammon, who consider all daily jumps in the U.S. stock market greater than 2.5%, up or down, since 1900. They classify the reason for each jump into 17 categories based on human readings of next-day (or same-evening) accounts in the *Wall Street Journal* (and *New York Times* in 2020). Fractional counts arise when newspapers differ in their jump attribution or human readers differ in their classification of the attribution. Number Attributed to Economic Fallout of Pandemics includes jumps on 3/12 and 3/16 that a subset of coders classified as Macroeconomic Outlook. It’s clear from reading these articles that the journalist regarded the deterioration in the Macroeconomic Outlook as due to the spread of the coronavirus.