What Triggers Stock Market Jumps?

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Abstract: We examine next-day newspaper accounts of large daily jumps in 19 national stock markets to assess their proximate cause, clarity as to cause, and geographic source. Our sample of over 8,000 jumps, reaching back to 1900 for the United States, yields several novel findings. First, jumps have become more grounded in readily perceived news developments over the past century. Second, news about monetary policy and government spending accounts for a highly disproportionate share of upward jumps. Third, upward jumps attributed to monetary policy and government spending shocks are much more likely after a stock market crash. In this sense, the "Fed put" emerged decades before the 1990s, characterizes fiscal policy as well, and extends to other countries. Fourth, jumps triggered by monetary policy foreshadow much lower volatility than other jumps. Finally, leading newspapers attribute 38 percent of jumps in their own national stock markets to US economic and policy developments. The US role in this regard dwarfs that of Europe and China.

JEL Codes: E44, E52, E62, F36, G12, G18

Keywords: stock market jumps, clarity about jump reason, monetary policy, government spending shocks, Fed put, global impact of US, market volatility, text analysis, human readings

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1. Introduction

What drives big moves in national stock markets? To address this question, we characterize contemporaneous perceptions of large daily market moves, describe how those perceptions vary across countries and time, and show that expressed perceptions have predictive power for market volatility. Our findings say that national stock market moves have, over time, become more grounded in readily perceived news events, that monetary and fiscal authorities generate shocks that (mostly) jolt equity markets to the upside, and that US economic and policy developments play a remarkably outsized role in stock markets around the world.

The benchmark view in economics and finance holds that stock price changes reflect rational responses to news about discount rates and cashflows. Under this view, we expect large daily moves to be accompanied by readily identifiable developments that affect discount rates and anticipated profitability. Moreover, contemporaneous news accounts should contain information about the proximate drivers of these moves. Of course, stock price behavior may not conform to the benchmark view. Keynes (1936), for example, famously argued that investors price stocks based not on their opinions about fundamental values but on their opinions about what others think about stock values. Even when speculative or irrational forces are in play, however, we expect contemporaneous news accounts to discuss the perceived drivers of big market moves. Thus, we turn to newspapers to distill information about what triggers big moves in national stock markets.

Specifically, we examine next-day newspaper accounts of big daily moves ("jumps") since 1900 in the United States, 1930 in the United Kingdom, and the 1980s in 17 other national markets. A threshold of 2.5 percent, up or down, for the US stock market yields 1,179 jumps from 1900 to 2023. These jumps account for 3.5 percent of trading days but nearly 20 percent of total daily variation (sum of absolute returns) and half of daily quadratic variation (sum of squared returns). Our jump thresholds for other countries range from 2 to 4 percent, with higher thresholds for markets with greater volatility. All told, we examine 8,049 daily stock market jumps across 19 national markets plus another 455 jumps in US bond markets from 1970 to 2020.

Jumps of the size we consider typically attract coverage in leading national newspapers. We locate and read articles (published before the market reopens the next day) about each jump to assess its proximate cause(s), perceived clarity as to cause, and the geographic source of the market-moving news. Our objective is to accurately characterize and code the journalist's explanation and interpretation of the jump. We rely on trained human readers to classify the reason for each jump into 17 categories, one of which is "Unknown & No Explanation." Readers also code the confidence with which the journalist advances an explanation for the jump and the ease or difficulty of coding the article. For the United States, we focus on next-day articles in the *Wall Street Journal*, *New York Times*, *Washington Post*, *Chicago Tribune, Financial Times*, and *Los Angeles Times*. We deploy many human readers to obtain multiple reads per jump and paper.[1] To quantify clarity about the perceived reason for each jump, we combine our data on journalist confidence, ease of coding, pairwise agreement across reads, and whether the journalist advances an explanation for the jump.

Previous studies also use news reports to evaluate the drivers of big national stock market moves. Classic studies by Niederhoffer (1971) and Cutler, Poterba, and Summers (1989) considered major jumps to assess whether they could be explained by identifiable news events, reaching mixed conclusions. Ferguson (2006) consults weekly commentaries and news articles to assess the role of war risks on sovereign bond yields in the seventy years before the outbreak of World War I. Our study advances on earlier work in several respects: scale, covering more than 8,000 jumps; scope, spanning 19 national markets and more than 90 years for the US and UK markets; granularity, detailing the jump reason and geographic origin of market-moving news; novel measurement, quantifying clarity as to jump reason; and volatility dynamics, investigating the relationship of jump reason and clarity to market volatility and the dispersion of firm-level returns.

For journalists observing the market in real time, attribution to a clear causal trigger is easy for many jumps and hard for others. To illustrate this point, Figure 1 plots intraday market values at 1-minute intervals on four US jump days. The top panels exhibit large, abrupt intraday moves associated with important news. In the top left, the market jumped over 3% after the Fed announced a surprise rate cut. In the top right, the market plunged 2.5% at open after an unexpectedly bad employment report. In contrast, the lower panels show two instances of large moves without a clear cause, and for which journalists advanced no explanation. In our US sample back to 1900, 17 percent of jumps occur for no identifiable reason, according to next-day newspaper accounts.

Leveraging our jump-day characterizations, we develop several novel findings. First, and unlike other jumps, the ones attributed to policy factors are more likely to be in the upward direction. This pattern holds in every country and has intensified over time in the United States and United

[1] Given the scale of our data collection efforts, we deployed more than 45 trained human readers comprised of the authors, graduate students, and undergraduate students. Baker et al. (2021) set forth our coding guide and reference manual. Our codings for the *Wall Street Journal* are at https://stockmarketjumps.com/research/.

Kingdom, the two countries in our sample with long-span coverage. Upward policy jumps are nearly twice as common as downward policy jumps from 1980 to 2023 in the United States. Over the same period, upward jumps attributed to other factors are only 60 percent as common as downward ones. To put the point another way, policy-related developments trigger 47 percent of upward US jumps since 1980 but only 22 percent of the downward jumps.

Drilling down, we find that news about monetary policy and government spending accounts for the predominance of upward moves among policy-driven jumps. A potential explanation is that large positive surprises about monetary policy and government spending occur more often after bad economic news, reflecting deliberate policymaker efforts to engineer offsetting shocks (Cieslak and Vissing-Jorgensen, 2021). Indeed, we show that the frequency and share of upward jumps attributed to monetary policy or government spending increase when stocks fall in the preceding three months. A 20 percent stock market drop, for example, raises the likelihood of an upward jump due to news about monetary policy or government spending by a factor of five. This pattern holds for every country we consider except Brazil and Turkey. In contrast, we find no evidence that stock market booms lead to downward jumps triggered by monetary policy or government spending.

A skeptic might interpret these patterns as artifacts of how journalists see the world and cover the news. Perhaps journalists are inclined to credit policy for upward jumps and to overlook policy mistakes that trigger downward jumps, and perhaps this type of bias manifests more powerfully after a period of falling stock prices. While we cannot rule out some bias in coverage, we validate our newspaper-based jump classifications with reference to FOMC announcements, macroeconomic statistical releases, national election dates, and the industry distribution of jump-day returns. All validation exercises support the view that our newspaper-based classifications capture forces that trigger jumps. Also, journalists show no general tendency to attribute upward jumps to policy factors. Instead, this pattern holds only for monetary policy and government spending.

Second, our jump classifications have predictive value for market volatility. In particular, jumps attributed to monetary policy are followed by less volatility than other jumps. For example, our conditional forecast of volatility over the two weeks after a jump due to monetary policy is lower than after other jumps by three-quarters of the time-series standard deviation of two-week volatility. This finding suggests that jump-inducing monetary policy actions resolve uncertainties in a manner that tamps down market volatility. Jumps attributed to other forces don't share this property. News about monetary policy triggers about 10 percent of all US jumps after World War II and a similar share of jumps across the other 18 national markets covered by our study.

Our third set of findings pertains to clarity about the reasons for market jumps. Our clarity measure fluctuates in a positively autocorrelated manner around a clear upward drift. Over the past 90 years, the share of jumps due to unknown forces fell from about 35 percent to 10 percent in both the United States and the United Kingdom. The other components of our clarity index – journalist confidence, pairwise agreement rates, ease of coding – tell a similar story. Thus, jumps have become better grounded in readily perceived news developments over the past century. This upward trend in jump clarity likely reflects a combination of more transparency about corporate performance, better statistical information about the economy, falling communication and information processing costs, and the professionalization of financial news reporting. Whether the size of jump-day returns also came to better reflect news about fundamentals is a distinct question that we do not tackle here.

Market volatility tends to be greater for at least two weeks before and after low-clarity jumps (as compared to high-clarity jumps). In this sense, high clarity and low volatility come together. Greater clarity about the jump reason also foreshadows less dispersion in firm-level equity returns. This is another respect in which our jump characterizations help predict market behavior.

In a final set of results, we show that news about US economic and policy developments exerts an extraordinary influence on equity markets around the world. Excluding the US stock market and focusing on the other 18 national markets covered by our study, news about US-related developments triggers 38 percent of all daily equity market jumps from 1980 to 2020 (41 percent when dropping jumps due to unknown forces and those with no next-day article). The US role in this regard dwarfs that of Europe as a whole, even though Europe accounts for a greater share of global output. News about economic and policy developments related to European countries and supranational European institutions seldom drives jumps in non-European countries, with the clear sustained exception of the European sovereign debt crises in the early 2010s. China-related news plays almost no role as a source of jumps in other countries before the mid-2000s but has since emerged as an important source of jumps outside China. Clarity as to jump reason is higher on average for jumps attributed to foreign developments.

Our study contributes to several literatures. A wide-ranging body of work considers how media coverage affects financial markets, with notable contributions by Tetlock (2007), Dougal et al. (2012), and Carlin et al. (2014), among others. Rather than media coverage effects on financial markets, we examine how journalists explain stock market jumps. In this respect, we are closer to Niederhoffer (1979) and Cutler, Poterba, and Summers (1989) and to more recent works by Manela and Moreira (2017) and Baker et al. (2025), who use newspapers to parse the sources of stock market volatility. Bybee et al. (2024) apply topic models to *Wall Street Journal* articles from 1984 to 2017 and study their usefulness in forecasting stock returns. Engle et al. (2020) use newspapers to measure climate change exposure risks, and Hassan et. al. (2019, 2024) use conference calls to quantify political risk exposures and their effects. Relative to these works, we show that news about monetary policy and government spending triggers a highly disproportionate share of upward stock market jumps, that monetary policy jumps foreshadow lower volatility, that the informativeness of newspaper accounts rose over time, and that news about US developments plays an outsize role in national stock markets around the world.

A related literature considers how the clarity of financial writing affects stock returns. Prominent works include Li (2008) and Shiller (2017). We contribute to this literature by developing a new approach to measuring clarity about the forces that drive market jumps. Our method is simple and transparent, which facilitates its application to other countries, periods, and markets. We also show that low-clarity jumps foreshadow more dispersion in firm-level returns. Our measurement approach opens the door to quantitative studies of how improvements in the accuracy, granularity, depth, and timeliness of economic statistics influence the extent of dispersion in firm-level returns and clarity about the forces that drive national stock market movements.

A large literature considers stock market reactions to news about future cash flows and discount rates. In addition to studies mentioned above, leading contributions include Shiller (1981) and Schwert (1989) for market-level moves and Roll (1988) for firm-level changes. Schwert shows that aggregate leverage, while correlated with market volatility, explains little of its movements over time. Many papers study the impact of news releases and central bank communications on financial market outcomes. Examples include Bernanke and Kuttner (2005), Birz and Lott (2011), Boudoukh et al. (2019), Cieslak and Schrimpf (2019), and Bianchi et. al. (2024). Compared to these papers, we proceed in the other direction by examining what drives stock (and bond) market jumps according to newspaper accounts. As remarked above, we offer new evidence related to the put-like character of monetary and fiscal policy responses to stock market developments.

Another literature focuses on the US Dollar and Fed policy in the international monetary and financial system. Prominent examples include Kalemli-Özcan (2019), Maggiori et al. (2019), Miranda-Agrippino and Rey (2020), Obstfeld (2021), and Gopinath and Stein (2021). These works highlight the US role as a global supplier of safe and liquid debt securities, the Dollar's favored status in foreign exchange reserves, the international spillover effects of US monetary policy, and the Dollar's ubiquity in trade invoicing, offshore bank lending, and portfolio holdings. We contribute to this literature by showing how to use newspapers to identify shocks in one country that propagate to equity markets in other countries. Our findings confirm the central role of the United States – its economy, currency, central bank, and military power – as a driver of national stock markets around the world. Our evidence differs in kind from related evidence in other studies, and it rests on distinct and complementary empirical methods.

Section 2 explains how we use newspapers to characterize stock market jumps, describes our jump classification scheme, and undertakes several investigations to assess the quality of our jump characterizations. Section 3 presents several findings about stock market jumps, including the put-like character of jumps attributed to monetary policy and government spending. Section 4 explains how we measure perceived clarity about the forces that drive jumps, documents empirical properties of our clarity measure, explains why clarity has risen over time, and provides evidence that greater clarity foreshadows less dispersion in firm-level equity returns. Section 5 concludes.

2. Data Creation, Quality Control, and Validation

2.1 Selecting Jumps and Locating Newspaper Articles

To assemble our sample of US jumps, we identify all days on which the CRSP Value-Weighted Total Market Index rose or fell by at least 2.5 percent (close to close, including dividends). Before 1926, we use the Global Financial Data (GFD) extension of the Dow Jones index. The 2.5 percent threshold yields 1,179 daily jumps from 1900 to 2023. These jump days account for 3.5 percent of all trading days, one-fifth of the absolute daily variation, and one-half of the daily quadratic variation over the 124 years covered by our study.

We chose the |2.5| percent threshold for reasons of practicality, informativeness, and the efficient use of human readers. In reaching this judgement, we examined next-day accounts for 389 trading days from 1945 to 2019 with market moves from |2.0| to |2.5| percent. Explanations for these smaller moves are harder for journalists to discern. In particular, the share of next-day accounts that offer no explanation for these moves is 17.2 percent, as compared to 9.6 percent for daily jumps greater than |2.5| percent in the same period. In another exercise, 43 percent of next-day accounts offer no explanation for the prior-day move in a small random sample of non-jump trading days. There is less to explain, and less to learn from newspaper accounts, when the market is quiescent. These results are perhaps unsurprising, but they confirm that the informativeness of newspaper accounts drops off sharply as we look beyond large daily moves. Accordingly, we focus our scarce human resources on trading days with jumps greater than |2.5| percent.

We search for next-day articles about each jump in six major US newspapers. During the internet era, articles often appear online after market close on the jump-day in question. Coders search for articles that mention phrases like 'stock market,' 'wall street,' 'S&P,' or 'Dow Jones' in the title, synopsis, or index of descriptive terms. They avoid summaries, abstracts, digests, and the like (i.e., articles with fewer than 300 words) when coding the jumps. If the search query yields multiple articles for a particular jump and paper, the coder selects the first one unless it proves uninformative. This process yields at least one article for all US jumps since 1900.

We follow the same approach for the United Kingdom. That is, we first identify all daily market moves that satisfy the |2.5| percent threshold and then search for next-day articles about the jump in question in four leading newspapers. To quantify daily moves in the UK market, we use GFD's "UK Industrials" index from 1930 to 1983, the FTSE 100 index from 1984 to 1993, and the FTSE 100 total return index from 1994 to 2020. Coders search for articles that contain terms like 'FTSE,' 'London stock exchange,' 'stock market,' 'equity market,' and 'share prices' to identify relevant articles. We mostly use articles longer than 300 words, but we relax this criterion in the early years for the *Financial Times,* which often contained short articles.

Outside the United States and the United Kingdom, we focus on articles published in one or two leading domestic newspapers of record for the country in question (e.g., the *Globe and Mail* and *Toronto Star* for Canada). For papers published in languages other than English, we rely on native speakers to identify, read, and code the newspaper articles. If the last trading day of the week occurs on a Friday or Saturday, we consider articles published before the market opens on the following Monday. We depart from the |2.5| percent threshold for about half the countries in our sample, selecting larger values for countries with greater daily market volatility. Appendix Table A1 reports the sample period, jump threshold, and newspapers for each country. The stock markets in Brazil and Turkey are so volatile that we examine only a random subset of their jumps.

2.2 Classifying Jump Reasons, Geographic Origin, Journalist Confidence, and More

Before reviewing and coding the articles that feed into our dataset, our research assistants studied our Data Construction Guide ("Guide"), underwent two half-day training sessions, and took a test involving 50 articles. We (the authors) previously coded these 50 articles, which serve as a screening device and training tool to ensure that our coders follow the Guide. Those who failed the test were thanked for their efforts and not invited to continue working for us. We also implemented other quality-control steps, as discussed below.

Having selected an article, the coder reviews it carefully and – based on the journalist's characterization – classifies the jump reason into one or more of the 17 categories listed in Table 1. The Guide set forth by Baker et al. (2021) defines each category, includes many examples, explains how to handle jumps attributed to multiple causes, and discusses boundary cases and other challenging articles.[2] We classify the primary reason for each jump into one of our categories and, when warranted by the article's discussion, list a secondary reason as well. If an article mentions multiple reasons for a given jump but does not clearly identify the most important one, we treat the order of appearance in the article as a tie breaker.[3]

To compute the jump-by-reason distributions in Table 1, we aggregate over reads and jumps as follows. First, for each read of a given jump we assign a value of 1 to the primary reason if there is no secondary reason. We instead assign 0.75 to the primary reason and 0.25 to the secondary reason if the reader designates both. Third, we compute the simple mean over all reads for a given jump to obtain the jump-level observation. Unless noted otherwise, we take this approach throughout the paper. We compute the simple mean over jumps to obtain the entries in Table 1.

We also record the geographic source(s) of each jump's primary reason, again based on the journalist's explanation. For instance, we code the United States as the geographic source for a US jump attributed to a Fed policy announcement, while we code the United Kingdom as the source for a US jump attributed to Britain's decision to exit the gold standard. The geographic source can

[2] We created a first version of the Guide based on our personal experiences in locating, reviewing, and coding articles about a few hundred jumps. We then undertook a pilot study in which several students located, reviewed, and coded articles in accordance with the Guide. We met these students regularly to discuss any challenges or ambiguities they faced in their work and to identify gaps in the Guide. These meetings led to many improvements in the Guide, including many more examples of how to code challenging articles. We do not include the pilot-study data in our analysis dataset. Even after the pilot study, we expanded the Guide as needed to more fully explain how to handle unusual or challenging articles.

[3] Coders can also designate a tertiary jump reason. That happens infrequently, and we do not use the tertiary reasons in our analysis.

consist of multiple countries (or a region of the world) for various reasons that include the outbreak of war between two or more countries, other developments that involve several countries, policy decisions by supranational institutions like the European Central Bank, or simply because the primary and secondary causes stem from different source countries.

We record four additional pieces of information for each article: First, 'Journalist Confidence' is the assurance with which the article advances an explanation for the jump, which we score on a three-point scale of 1 for low confidence, 2 for medium confidence, and 3 for high confidence. For example, if an article asserts without qualification that bad news about corporate earnings drove a downward jump, Journalist Confidence is high. Second, 'Ease of Coding' reflects the ease or difficulty of discerning and classifying the primary jump reason, also scored on a three-point scale. While Ease of Coding correlates with Journalist Confidence, they are distinct concepts. For example, a journalist may confidently assert an explanation that involves multiple causes that touch on several of our categories. In this case, the primary jump reason may be hard to discern and classify, even though Journalist Confidence is high.[4] Third and fourth, the coder paraphrases the journalist's explanation in one field and, in another field, separately records the key passage that forms the basis for classifying the primary jump reason.[5] For example, when the primary jump reason is Taxes, the key passage might say, "The completion of a tax deal between the White House and Congress sent stocks soaring Wednesday."

2.3 Additional Examples

To appreciate how our data creation process works in practice, it is useful to consider a few more examples. The top left panel of Figure 2 displays an excerpt from an article about the upward jump on 18 April 2001. We classify the reason for this jump as Monetary Policy and Central Banking, because the article title and first sentence attribute the jump to a "*surprise rate cut*" by the Federal Reserve. Since the Fed is a US policy institution, the geographic source is the United States. Journalist confidence is "high," because the article forcefully and unambiguously attributes the jump to the Fed's decision. Ease of coding is "easy," because the article is easy to comprehend, the jump reason is easy to discern, and the mapping to our classification of jumps by reason is straightforward. The

[4] The Guide contains many examples that illustrate how to score Journalist Confidence and Ease of Coding.

[5] The third and fourth pieces of recorded information are especially useful for later refinements. For example, we used them in Baker et al. (2020) to quickly identify, quantify, and characterize US jumps triggered by pandemics and infectious diseases from 1900 to 2020.

lower right panel of Figure 2 displays an excerpt from an article about the downward jump on 2 July 2009. This article makes clear in the title and first sentence that an "*unexpectedly gloomy jobs report*" triggered the downward jump, which we classify under Macroeconomic News & Outlook. The United States is the geographic origin, journalist confidence is "high," and coding is "easy."

Figure 3 displays excerpts from two articles about a 5 percent upward jump on 26 December 2018. We classify the jump reason as Unknown for the *Wall Street Journal* article, because the reporter writes, "*investors and traders were left scratching their heads to explain the wild swings*." This passage appears in the third paragraph, reflecting a common practice of placing less-assured explanations further down the article. Since the article says the jump is due to unknown forces, we leave the geographic origin blank. For the *New York Times* article, we classify the primary jump reason as Macroeconomic News & Outlook based on "*early reports of a strong holiday-shopping season helped lift the S&P 500 by nearly 5 percent.*" Other papers offer various explanations for this jump. For example, the *Los Angeles Times* offers three explanations over nine paragraphs, including "*a late report that a US government delegation will travel to China*." Overall, the jump on 26 December 2018 is a low-clarity event in that some papers explicitly attribute it to unknown forces, others offer a variety of reasons, and newspapers disagree in how to interpret the jump. Journalists also present their explanations for this jump with less assurance and more qualifying language. Section 4 below explains how we integrate these aspects of newspaper coverage to quantify clarity about the reason for this jump and others.

2.4 Quality Control and Validation

As shown in Figure A1, we typically identify and code articles in four to six newspapers for each US stock market jump and obtain eight to ten distinct reads per jump. If the human coders initially disagree about the reasons for a particular jump and newspaper, we revisit that case in a group meeting. Disagreements are more common for jumps that are harder to classify and when the journalist expresses less confidence about the jump reason. In some cases, a disagreement reflected a misreading of the article by one coder or a failure to follow the Guide. In these cases, we amended the coding to reflect a correct reading that adheres to the Guide. In other cases, there is a genuine lack of clarity in the article about the jump reason (or an ambiguity in how to map the journalist's explanation into our categories). In these cases, we sought other articles about the jump in the same paper. If we found a suitable article and it resolved the ambiguity, we used it to resolve the disagreement. Otherwise, we let the original classifications stand, effectively letting the coders agree to disagree. Our final dataset reflects these disagreement cases.[6]

We turn now to some evidence on the consistency and reliability of our jump classifications. Table 2 reports information on pairwise agreement rates across coders and newspapers with respect to the primary jump reason. Consider the "Within WSJ" row, which restricts attention to jump classifications based on articles in the *Wall Street Journal*. The average pairwise agreement rate is 78.0% across our seventeen granular jump-by-reason categories and 92.5% between "Policy" and "Non-Policy" in the period from 1980 to 2023. It is slightly lower from 1900 to 1979. Thus, WSJ articles yield highly consistent jump-by-reason classifications across human readers. Pairwise agreement rates are somewhat lower within the other newspapers, which aligns with our broad impression that WSJ articles tend to be more clearly written.

When looking across coders *and* newspapers (for the same jump), pairwise agreement rates drop markedly – especially for the granular categories, and more so in the earlier period. This result reflects the fact that newspapers sometimes differ in their explanations for a given jump. Disagreement rates are higher in the early decades of our sample. Nevertheless, all agreement rates reported in the top panel of Table 2 are much higher than would obtain from a random assignment of jump reasons under the unconditional jump-by-reason distribution.

If our jump-by-reason assignments reflect objective developments, then jumps attributed to category X should occur more often in reaction to the arrival of information about X. For instance, we expect jumps attributed to Macroeconomic News & Outlook to occur more often in reaction to statistical releases about inflation, employment growth, and jobless claims. Likewise, we expect US jumps attributed to Elections & Political Transitions to occur more often after US federal elections than after other days, and we expect jumps attributed to Monetary Policy & Central Banking to occur more often after FOMC meetings. We test these propositions in Table 3 and find strong support for all three of them. For example, US jumps attributed to Monetary Policy & Central Banking occur with much greater frequency the day of or after FOMC meetings. Jumps attributed to this category

[6] Aside from the United States and United Kingdom, we often had only one or two readers per country. That made it infeasible to use pairwise disagreement as a quality-control tool. Thus, we took a different approach for these countries: We reviewed the entries for each jump to ensure that the paraphrased explanation and the key quoted passage support the jump classification. If not, or if there was doubt, we asked the coder to translate passages from the underlying article, which we then read. If warranted, we then amended the coding.

do not occur with greater frequency in the wake of federal elections or statistical releases about inflation, employment growth, and jobless claims.[7]

We implement another approach to testing whether our jump-by-reason assignments reflect objective developments in the appendix. We first observe that, for some daily stock market jumps, the explanation offered in next-day newspaper accounts implies an amplified or dampened response of equity returns in certain industries. We then investigate whether industry-level stock returns on these jump days exhibit the pattern of amplification and dampening implied by the jump-by-reason attribution. They do, as reported in Table A2. These results also support the view that our newspaper-based jump attributions reflect objective developments.

In short, all validation exercises align with the view that our jump-by-reason attributions reflect objective developments. In Section 4.2 below, we implement other validation exercises that support this conclusion. We will also show that our jump-by-reason attributions have predictive value for post-jump market volatility and cross-sectional dispersion in firm-level returns. These results also support the view that our newspaper-based characterizations contain useful information about what triggers stock market jumps, and that these characterizations are not simply artifacts of journalistic preconceptions or a tendency to attribute the jump to salient news.

3. Characterizing Daily Jumps in National Stock Markets

3.1 Jump Frequency Over Time

There is much variation over time in the frequency of jumps and the forces that trigger them. Figure 4 reports daily jumps per year in the United States from 1900 to 2023, with a breakdown into three broad categories: policy developments, non-policy developments, and unknown forces. Policy developments include Taxes, Regulation, International Trade Policy, Sovereign Military & Security Actions, and other policy-related categories. Non-policy developments include Corporate Earnings & Outlook, Commodities, Terrorist Attacks & Non-State Violence, and more.

The early years of the 20th century feature high volatility, punctuated by banking panics in 1901, 1903, and 1907. The Great Depression era, from 1929 to the late 1930s, stands out for an extraordinary volume of daily jumps. Perhaps surprisingly, jump frequency is only modestly

[7] The triangular structure of coefficients in Table 3 reflects data availability for the explanatory variables. We can date US federal elections back to 1900, but the recurring statistical releases we consider began in 1953 and regularly scheduled FOMC meetings began in 1994.

elevated during and after World War II, despite the cataclysmic events of that period. The period around the Korean and Vietnam Wars also has few jumps.[8] More broadly, the first quarter century after World War II produced long stretches with few daily moves large enough to cross our jump threshold. Jump frequency is high during the Tech boom and bust in the late 1990s and early 2000s. The Global Financial Crisis saw the greatest number of jumps since the 1930s, followed by another quiescent period with only 2.9 jumps per year from 2012 to 2019. The coronavirus pandemic brought 36 jumps in 2020 alone. In fact, the period from 24 February to 24 March 2020 contains 18 jumps over 22 trading days, more than any other one-month period back to 1900.[9]

Figure A2 displays the same type of chart using data on daily stock market jumps for the United Kingdom back to 1930. There are striking differences relative to the United States and some similarities. The UK stock market experienced a much lower jump frequency in the 1930s than the US market, reflecting a milder depression in the United Kingdom. However, the UK market experienced a huge number of jumps in the mid 1970s in connection with high inflation, large government budget deficits, balance-of-payments deficits, and the 1976 Sterling Crisis. Like the United States, the United Kingdom saw high jump frequency during the Tech boom and bust, the Global Financial Crisis, and in reaction to the coronavirus pandemic.

3.2 What Triggers National Stock Market Jumps?

Table 1 reports the distribution of daily stock market jumps by reason in the United States from 1900-2023, the United Kingdom from 1930-2020, and in 17 other national markets from 1980 onwards.[10] Macroeconomic News & Outlook accounts for one-quarter to one-third of all jumps in our sample, depending on period and country. The second-most common category is Corporate Earnings & Outlook, following by Monetary Policy & Central Banking and Government Spending. Stock market jumps triggered by "Sovereign Military & Security Actions" are rare since 1980 but a prominent source of jumps in the first half of the 20th century, especially during World Wars I and II. Commodities are also an important source of US jumps in the early part of the 20th century, when

[8] Schwert (1989) highlights low stock market volatility in wartime and dubs it the "war puzzle." Cortes et al. (2024) provide evidence that stable demand from defense spending during wartime makes it easier to predict US corporate cash flows, which helps to understand the phenomenon.

[9] Baker et al. (2020) offer historical perspective on US stock market jumps in the early months of 2020, and Davis et al. (2021) show that these jumps coincide with hugely dispersed firm-level stock returns.

[10] Australia, Brazil, Canada, China (Hong Kong), France, Germany, Greece, India, Indonesia, Ireland, Japan, New Zealand, Singapore, South Africa, South Korea, Spain, and Turkey. The appendix compares our jump-by-reason attributions to the ones in Cutler, Poterba and Summers (1988).

agriculture accounted for a much larger share of GDP. Jumps attributed to Regulation featured prominently during the New Deal period. Monetary Policy & Central Banking is somewhat more important as a source of US jumps in more recent decades.

We draw several inferences from this table. First, policy news drives a large fraction of daily stock market jumps. Over 36% of US jumps reflect policy developments, more than macro news (23.5%) and corporate news (11.2%) combined. Globally, policy-related developments account for 28% of jumps. Second, the jump-by-reason distributions are broadly similar across the US, UK, and Rest of the World (ROTW). Foreign Stock Markets are the third-most common driver of jumps in the ROTW, partly reflecting the perceived role of US stock markets as drivers of global markets.[11] Third, newspapers offer no explanation for many jumps, sometimes stating explicitly that the reason is unknown. Fourth, relative to equity markets, bond market jumps are much more dominated by Macroeconomic News & Outlook and news about Monetary Policy & Central Banking. These two categories account for 73% of US Treasury bond market jumps from 1970 to 2020.[12]

Figure A3 shows the evolution of cumulative log returns for jump days, other days, and selected jump categories. Cumulative returns drift up for other days and down for jump days. Within the set of jump days, the return pattern differs sharply across categories. Specifically, cumulative returns drift up for jumps attributed to Monetary Policy & Central Banking, Government Spending, and Other Policy (not shown). They drift down for all other jump categories, including all non-policy categories. As we will show, jumps attributed to Monetary Policy & Central Banking and to Government Spending are also quite distinctive in other respects.

3.3 The Geography of News that Triggers National Stock Market Jumps

We turn now to the geography of news that triggers national stock market jumps. Figure 5 plots the geographic source of jumps in the US market, revealing the predominance of US-related news for US jumps. Eighty-nine percent of US jumps from 1900 to 2023 reflect US-related developments (omitting jumps attributed to unknown forces), according to next-day accounts in leading US newspapers. Europe's role as a source of US jumps is modest outside of World Wars I

[11] We designate the jump reason as Foreign Stock Markets only when "News reports … attribute a large domestic market move directly to foreign stock-market moves ***without*** offering any deeper explanation for the domestic or foreign stock market move." (Quoting from our coding guide.)

[12] We define bond market jumps as daily changes of more than 15 basis points in the yield on 10-year constant-maturity Treasury bonds. We read and coded only a 25% random sample of bond market jumps between 1980 and 1982, when yields were quite high and volatile.

and II and the European sovereign debt crises in the early 2010s. The increased role since 2010 for news related to Asia as a source of US jumps largely reflects the growing influence of China. For "Other" geographic sources of US jumps, the main region in play is the Middle East in connection with the OPEC oil shocks in the 1970s and Gulf Wars I and II. UK developments are the predominant source of jumps in the UK stock market through the 1970s (Figure A4). Since then, developments sourced to the United States account for roughly the same share of UK jumps as developments sourced to the United Kingdom itself.

Figure 6 plots the share of jumps attributed to US-related and Europe-related news in other countries: Australia, Brazil, Canada, India, Indonesia, Hong Kong, Japan, New Zealand, Singapore, South Africa, and South Korea. Remarkably, leading newspapers in these countries attribute, on average, 40% percent of daily jumps in their own national stock markets to US-related developments. In contrast, they attribute only 7 percent of their jumps to Europe-related developments, even though aggregate output across all European countries is fifty percent greater than US output on a PPP-adjusted basis. US developments are an especially important source of jumps in other countries during the Global Financial Crisis, and they are as important since then as in the 1980s and 1990s. The outsized role of US-related news as a source of jumps also holds when we consider European markets (not shown). In contrast, China-related developments rarely trigger jumps outside its own borders before 2004 (Figure A5). Since 2004, China-related developments often trigger ten percent of more of stock market jumps in other countries.

These results underscore the central role of the United States – its economy, the Dollar, US Treasury securities, Fed monetary policy, and US military power – in the global financial system. No other country or region plays a comparable role as a source of news that drives national stock market jumps around the world. In this respect, our results deepen and extend Ehrmann et al. (2011), who find that spillovers from US bond, equity, and money markets to European markets are much larger than the other way around. Our evidence says the US role in this regard is at least as important in the 21st century as in the 1980s and 1990s. The Tech bust, Iraq invasion, and Global Financial Crisis stand out for an especially high share of stock market jumps attributed to US developments. Concurrent research by Boehm and Kroner (2024) shows that surprise components of U.S. economic news releases move stock market indexes around the world in the period from 1996 to 2019. Like us, they find a stark asymmetry in that US news matters much more for foreign stocks than foreign news matters for US stocks. Other concurrent research by Rey et al. (2024) highlights the Dollar's role in transmitting US news to exchange rates and to foreign equity markets.

3.4 How Upward and Downward Jumps Differ

Appendix Tables A3 and A4 document some sharp distinctions between upward and downward jumps. Among jumps triggered by policy-related developments, upward moves outnumber downward ones in every country. In contrast, downward moves are much more prevalent among jumps triggered by non-policy developments. As it turns out, this preponderance of upward moves among policy-driven jumps is entirely due to news about monetary policy and government spending. For the roughly one-sixth of all jumps across all countries attributed to these two policy categories, 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.

Figure 7 reveals an even more striking feature of US jumps: The greater the jump-day return, the greater the share of jumps attributed to monetary policy or government spending. This pattern also holds in the rest of the world (Figure A6). For the United States and United Kingdom, the pattern is even stronger since 1980 than in earlier decades (Figures 7 and A7). It's also worth noting that the mix of policy-driven US jumps shifted away from Sovereign Military & Security Actions and Regulation after the first half of the 20^{th} century (Table A4), leading to an even greater preponderance of upward moves among all US jumps triggered by policy news.

3.5 The Put-Like Character of Jumps Due to Monetary and Government Spending

These results raise an obvious question: Why are large daily stock market reactions to news about monetary policy and government spending so skewed to the upside? One hypothesis is that monetary and fiscal authorities seek to engineer positive shocks in reaction to a deterioration in market conditions, and they succeed more often than not. Prominent examples of such behavior include the Fed's liquidity support for the financial system after the October 1987 stock market crash, policy responses to the Global Financial Crisis of 2008-09 by leading monetary and fiscal authorities around the world, the European Central Bank's reaction to Euro-area sovereign debt crises in the early 2010s, and highly aggressive policy responses by monetary and fiscal authorities to the coronavirus pandemic of 2020-21.

To evaluate this hypothesis, we investigate how jumps attributed to monetary policy and government spending relate to prior market returns. Let MP_t be the share of codings attributed to Monetary Policy & Central Banking for a jump that occurs on day t. For example, if all readers attribute the day-t jump to monetary policy, then $MP_t = 1$. Similarly, let GS_t be the share attributed to Government Spending. Define $NET(MP_t + GS_t)$ as the sum of MP_t and GS_t for upward jumps and minus one times the sum for downward jumps. Figure 8 displays bin scatters of $NET(MP_t + GS_t)$ on own-country national stock market returns over the prior 66 trading days (three calendar months) for US jumps from 1900 to 2023 and for 17 countries from 1980 to 2020.

Both panels in Figure 8 reveal clear evidence that stock market drops foreshadow upward jumps attributed to monetary policy or government spending. In this regard, three features of Figure 8 warrant attention. First, most of the data points are in the upper left quadrant. That is, stock market jumps attributed to monetary policy or government spending are more likely after the stock market falls, and these jumps are typically in the upward direction. Second, the greater the stock market fall in the preceding 66 trading days, the greater the likelihood of an upward jump attributed to monetary policy or government spending. Third, market gains in the preceding 66 trading days do not lead to jumps attributed to monetary policy or government spending.

Table 4 provides quantitative information about these patterns. Panel A considers US data from 1900 to 2023. Column (1) reports a regression of $NET(MP_t + GS_t)$ on cumulative market returns over the preceding 66 trading days using a specification that mirrors the bin scatter in Figure 8. The slope coefficient of -0.29 implies that a 20 percent drop in the US market raises $NET(MP_t + GS_t)$ by 5.8 percentage points.[13] This effect dwarfs the mean value of $NET(MP_t + GS_t)$ on jump days, which is only 0.2 percentage points.

Column (1) tells us how jump attributions relate to prior market performance, conditional on a jump occurring. Perhaps more interesting is how prior market performance relates to unconditional jump likelihoods. To address this question, we expand the sample to include all trading days, setting $NET(MP_t + GS_t)$ to zero on non-jump days. Consider column (2) in Panel A. The slope coefficient implies that a 20 percent market drop raises $NET(MP_t + GS_t)$ by 2.8 percentage points. This effect equals 81 percent of the unconditional jump likelihood (regardless of reason or direction) and 173 percent of the unconditional likelihood of an upward jump (regardless of reason). It is 5.7

[13] We ignore the (small) regression intercept shift in this calculation.

times the unconditional likelihood of a jump triggered by monetary policy or government spending. In sum, stock market drops over the preceding three months foreshadow a sharply heightened likelihood that monetary policy or government spending triggers an upward jump.

This form of countercyclicality in policy-driven stock market jumps also holds for other countries in our sample, with the notable exceptions of Brazil and Turkey. To make this point, Panel B in Figure 8 shows a bin scatter of $NET(MP_t + GS_{\mathrm{t}})$ on own-country national stock market returns over the preceding 66 trading days in data pooled over 17 countries.[14] In this sample as well, stock market drops foreshadow upward jumps due to monetary policy and government spending, but prior market gains do not foreshadow downward jumps triggered by these sources. Returning to Table 4, column (2) in Panel B implies that a 20 percent stock market drop raises $NET(MP_t + GS_{\mathrm{t}})$ by 2.8 percentage points, which equals 74 percent of the unconditional jump likelihood, 158 percent of the unconditional likelihood of an upward jump, and 4.7 times the unconditional likelihood of a jump triggered by monetary policy or government spending.

The put-like character of policy responses to stock market movements holds for both monetary policy and government spending – and in both samples. See columns (3) to (6) in Table 4. These put-like policy responses have strengthened over time, at least in the United States and United Kingdom, as shown in Table A5. The UK and US results for the period since 1980 imply that a 20 percent stock market drop raises the unconditional likelihood of a jump triggered by monetary policy or government spending by a factor of roughly ten. This evidence suggests that the US and UK monetary and fiscal authorities have become more effective at engineering positive news shocks in the wake of stock market declines.

The results in Figure 8, Table 4 and Table A5 complement and broaden important findings in previous research on "the economics of the Fed Put." Cieslak and Vissing-Jorgensen (2021) focus on monetary policy in the United States since the mid 1990s and show, first, that stock market declines predict monetary policy easing actions and, second, that FOMC policymakers pay attention to stock market performance in their policy deliberations. Using a different identification strategy, Rigobon and Sack (2003) find that stock market drops predict cuts in the Fed's policy rate. Our evidence shows that the economics of the Fed put is not a recent-to-emerge phenomenon, nor is it

[14] Figure A8 displays bin scatters for Brazil and Turkey. They differ sharply from the ones in Figure 8. Monetary policy has been politically contentious in Brazil and Turkey and sometimes driven by strong fiscal pressures. Both countries had extreme stock market moves during hyperinflation episodes. These factors perhaps explain why Brazil and Turkey do not show the same pattern as other countries in our sample.

restricted to the United States. Instead, the economics of the central bank put operate broadly across countries that pursue technocratic policy. It is a feature of fiscal policy as well.

Monetary policy relates to asset price behavior in other distinctive ways as well. For example, Lucca and Moench (2015) show that US stocks exhibit large average excess returns in the hours leading up to scheduled FOMC announcements. While concentrated in short windows of time, these excess returns account for about eighty percent of total realized equity returns from 1994 to 2011. When Lucca and Moench consider other major US economic news releases, no similar pattern emerges. Hillenbrand (2024) finds that the entire secular decline in ten-year US Treasury yields from June 1989 to June 2021 occurs within three-day windows around FOMC meetings.

3.6 Differences in Post-Jump Market Volatility by Jump Reason

We have shown that the distribution of stock market jumps by reason varies over time, across countries, and with prior market returns. We now ask whether the contemporaneously perceived jump reason has predictive content for post-jump market volatility. We find that it does, even when we condition on jump size and direction and market volatility in the days and weeks leading up to the jump. Our chief finding in this regard is that jumps triggered by news about monetary policy foreshadow much less post-jump volatility than other jumps.

To highlight this finding, we fit regressions on daily US data from 1900 to 2023:

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

where r_t is the return on day *t* in the CRSP value-weighted index, and the dependent variable is realized daily volatility over *n* days after *t*. As before, MP_t is the fraction of codings attributed to Monetary Policy & Central Banking on day *t* for jump days, and zero otherwise. We define $Other_t$ analogously for the collection of other jump reasons. The omitted category is days with no jump. We control for positive and negative returns on day *t* (following Black, 1976) and so-called "HAR" variables that capture past volatility over multiple look-back horizons (following Corsi, 2009).

Figure 9 plots the estimated *g* and *h* coefficients and their 95 percent confidence intervals for $n = 1,2, \dots 22$ trading days after a jump day. Jumps triggered by monetary policy foreshadow an absolute reduction in market volatility (conditional on controls). This effect is statistically significant at the 95 percent level for trading days 2 through 8 after the jump and marginally significant for at least a month. The monetary policy effect on post-jump volatility is even greater relative to jumps triggered by other forces. 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. Appendix Figure A9 shows that the volatility-dampening aspect of monetary policy news is much stronger in recessions.

These results show that market-moving news about monetary policy tends to dampen uncertainty – absolutely, and especially as compared to other jump-generating news. One potential interpretation is that FOMC meeting announcements 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 macroeconomic statistical releases do not systematically reduce short-rate uncertainty, which again aligns with our evidence.

4. Jump Clarity and Stock Market Volatility

4.1 Quantifying Clarity as to Jump Reason

Journalists find it easy to discern the proximate reason(s) for some stock market jumps and hard for others, as illustrated by the examples in Figures 1 to 3. To capture and quantify this aspect of jumps, we create four measures of perceived clarity (as to the reason) for each U.S. jump:

i. <u>Pairwise Agreement</u>: Recall that we have multiple reads per jump. Because jumps of higher (lower) clarity tend to produce more (less) uniformity across reads in the jump-by-reason attributions, we use the average pair-wise agreement rate across reads for a given jump as a measure of its clarity.[15]

ii. <u>Journalist Confidence</u>: We also code the confidence with which the journalist advances an explanation for each jump. When the proximate reason for a jump is crystal clear, journalists

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[15] When both reads in a pair classify the reason as Unknown & No Explanation, we treat it as a case of disagreement. This practice avoids treating hard-to-explain jumps as high-clarity events.

typically assert an explanation with confident, assertive language. Thus, we use mean journalist confidence (across reads) as another measure of jump clarity.

iii. Ease of Coding: When discussing jumps that are harder to explain, journalists tend to use more roundabout language and to place any claims about the cause deeper in the body of the article. As a result, it's often harder for the human reader to discern the journalist's interpretation of jumps that are harder to explain. Thus, we use ease of coding as a third measure of jump clarity, with greater ease corresponding to higher clarity.

iv. Known Reason: Our last measure of jump clarity is perhaps the most obvious. For a given jump, we simply compute the fraction of reads that attribute the primary jump reason to some category other than Unknown & No Explanation.

We combine these four measures into an overall Clarity Index as follows: Normalize each clarity measure to mean zero and unit standard deviation over time. Sum these normalized measures and re-normalize the resulting sum to mean zero and unit standard deviation.

4.2 Jump Clarity and Intra-Day Concentration of Market-Level Moves

Figure 1 suggests that jumps with an obvious trigger often involve abrupt market moves in short time intervals. Thus, we expect greater intra-day concentration of jump-day returns to be associated with greater clarity about the jump reason. To test this view, we measure the intra-day concentration of market-level return movements as follows: First, calculate absolute returns over each 15-minute interval from the previous-day close to 9:45 am, 9:45 am to 10 am, and so on through the last 15-minute window from 3:45 pm to market close at 4:00 pm. Second, divide the largest absolute move among these trading intervals by the total distance travelled, defined as the sum of absolute market moves over these 15-minute intervals. This yields an intra-day concentration measure that ranges from 1/26 (for equal-size moves in each 15-minute interval) to 1 (when the full day's move occurs in a single 15-minute interval). We then regress this intra-day concentration measure on our Clarity Index and each of its components.

Table 5 reports the results using data from 1985 to 2023, which reflects the availability of high-frequency data on stock returns. According to the results in column (1), a two standard deviation increase in our Clarity Index involves a 0.64 standard deviation rise in the intra-day concentration of market-level returns. This finding confirms that jump days with higher intra-day concentration of market-level moves involve greater clarity about what triggered the jump. Column (2) shows that controls for jump size and direction and prior market volatility yield only a modest attenuation in the relationship of intra-day concentration to the Clarity Index. Columns (3) to (6) show that three of the four index components also exhibit statistically significant relationships to intra-day concentration in the expected direction.

In sum, Table 5 shows that high-clarity jumps are associated with concentrated intra-day movements in stock market returns, facilitating an easy attribution of the daily jump to a particular causal trigger. This finding confirms that our Clarity Index reflects how readily, and confidently, contemporaneous observers can explain stock market jumps. It also suggests that intra-day concentration could itself serve as a proxy for clarity about the reason for jumps. While intra-day concentration is easily automated, our Clarity Index offers two advantages. First, it is computable even when high-frequency stock returns data are unavailable, which is the case for most countries and time periods covered by our study. Second, our reliance on human readings yields granular jump-by-reason classifications. As we discuss next, clarity differs systematically by jump reason.

4.3 Jump Clarity, Jump Reason, and Market Volatility

Section 3.6 shows that our jump-by-reason classifications help predict post-jump volatility. We now investigate whether jump clarity helps predict volatility. To do so, we regress post-jump market volatility on the jump's Clarity Index value in Table 6. The dependent variable in columns (1) to (3) is the realized volatility of market-level returns over the first five trading days after the jump day, measured as the five-day sum of daily squared market-level returns. Column (1) implies that a two standard deviation drop in clarity involves a realized volatility rise of 8.7 units, or 0.17 standard deviations. Thus, harder-to-explain jumps foreshadow greater volatility.[16] Column (2) in Table 6 shows that controls for jump size and direction have little effect on the association between clarity and post-jump market volatility. However, when adding a battery of controls for pre-jump market volatility in column (3), the coefficient on the Clarity Index shrinks by more than half and is no longer statistically significant.

To visualize and more fully characterize the relationship between jump clarity and market volatility, we sort jumps into groups defined by high and low values of the Clarity Index. We then plot average daily volatility around jump days separately for each group in Figure A10. Market volatility is greater after and especially before low-clarity jumps (as compared to high-clarity jumps).

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[16] This result resonates with evidence for a different asset market in Carlin, Longstaff and Matoba (2014). They find that more disagreement among Wall Street mortgage dealers about mortgage pre-payment rates predicts higher return volatility on mortgage-backed securities.

The volatility gaps between low- and high-clarity jumps persist for ten or more trading days on either side of jump days. These gaps are statistically significant and sizable, ranging from 15-24 percent of average volatility in the 3 to 10 trading days before jumps and from 8-10 percent in the 3 to 10 trading days after jumps. The overarching story that emerges from these results is one of positive co-movement between market volatility and clarity: Periods of greater stock market volatility involve less clarity about the drivers of daily stock market jumps.

Table 6 also provides evidence on how clarity relates to the post-jump dispersion of firm-level stock returns. We measure dispersion by the daily value-weighted cross-sectional standard deviation of firm-level returns, averaged over the five trading days after the jump. According to column (4), a two standard deviation drop in the Clarity Index involves a rise in firm-level returns dispersion of 0.56 units, i.e., a 0.43 standard deviation increase. Column (5) shows that controls for jump size and direction matter little for this relationship. When we add a battery of controls for pre-jump returns dispersion (analogous to our HAR controls), the coefficient on the Clarity Index shrinks by more than sixty percent but remains statistically significant. In short, low-clarity jumps foreshadow greater market-level volatility *and* greater dispersion in firm-level returns.

Next, we turn to the relationship between jump clarity and jump reason. For the sake of brevity, we summarize the patterns in this regard with a regression of jump Clarity Index values on jump indicator variables, fit by least squares to US jumps from 1900 to 2023:

$$\underset{}{Clarity_j} = \underset{(0.04)}{0.22} + \underset{(0.09)}{0.39}MP_j + \underset{(0.10)}{0.14}GS_j + \underset{(0.08)}{0.67}SovMil_j + \underset{(0.08)}{0.00}\, OthPolicy_j - \underset{(0.06)}{1.83}\, Unknown_j$$

where MP_j is the share of reads for jump j attributed to Monetary Policy & Central Banking, GS_j the share attributed to Government Spending, $SovMil_j$ the share to Sovereign Military & Security Actions, $OthPolicy_j$ the share to all other policy categories (Regulation, Elections & Political Transitions, Taxes, Exchange Rate Policy & Capital Controls, International Trade Policy, and Other Policy) and $Unkown_j$ the share attributed to Unknown and No Explanation. The omitted group collects the six non-policy categories listed in Table 1.[17]

[17] We fit this regression by OLS to 1,172 jump-level observations based on human readings of next-day *Wall Street Journal* articles. The R-squared value is 0.50. It is 0.51 when adding controls for jump size, jump direction and realized market volatility over the prior 1, 5, and 22 trading days. These controls have modest effects on the magnitude and significance of the estimated coefficients. We lose five jump-level observations because we could not locate a next-day article and two due to missing values of the control variables.

Two jump categories exhibit strong relationships to jump clarity.[18] First, jumps attributed to Monetary Policy & Central Banking involve greater clarity than non-policy jumps. The coefficient on MP_j says this effect equals 0.39 standard deviation Clarity Index units. Since the coefficient on $OthPolicy_j$ is a precisely estimated zero value, jumps attributed to Monetary Policy & Central Banking also involve greater clarity than most other policy-related jumps. Putting this result together with earlier findings yields a novel characterization of how monetary policy shocks relate to stock markets. Specifically, jumps triggered by news about Monetary Policy & Central Banking are predominantly in the upward direction (Table A4), much more likely to occur after a large stock market drop in the prior three months (Table 4 and Figure 8), exert a dampening influence on stock market volatility over the next month (Figure 9), and are perceived with greater clarity than jumps attributed to other forces except for Sovereign Military & Security Actions.

That brings us to the second finding summarized in the regression: Jumps attributed to Sovereign Military & Security Actions involve greater average clarity than non-policy jumps and, indeed, than any other jump-by-reason category. Unlike monetary policy jumps, however, jumps triggered by news about Sovereign Military & Security Actions are predominantly in the downward direction (Table A4) and foreshadow more volatility (Table A6).

4.4 Information Quality and Jump Clarity over Time

Rising stock market capitalization raises the demand for factual reporting and analysis of market-relevant news. Perhaps partly in response, the quality, scope, and timeliness of statistical information about the US economy have improved tremendously over the past century. As a leading example, consider the BLS Monthly Employment Situation Report, a closely watched statistical release that is well known to move stock markets.[19] This report draws on data from two primary sources: Current Employment Statistics (CES) and the Current Population Survey (CPS). The CES program began in 1915 as a sample of convenience with data for 200 large manufacturing firms.[20] The BLS introduced formal sample design methods into the CES program around 1950 – followed by significant improvements in sample design in 1964, annual benchmarking to universe-level employment data in 1982, and the implementation of a probability-based sample design in 1995.

[18] Given our construction of the Clarity Index, its negative relationship to jumps classified as Unknown and No Explanation is mechanical. See Section 4.1.

[19] See, for example, Flannery and Protopapadakis (2002) and Andersen et al. (2007).

[20] See Johnson (2016), Kelter (2016) and Mullins (2016).

Sample sizes grew over time, reaching about 620,000 worksites in 2016. The CPS also saw major improvements in data quality, scope, scale, and timeliness from the 1940s onwards. See U.S. Census Bureau (2019) for a chronology. The upshot is that 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 that contain information about the economy and business outlook.

Information also became easier to access and cheaper to process. In this regard, 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 its staggered implementation, 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 the volume and accuracy of information produced by sell-side analysts. These advances over time in the scale, quality, scope, timeliness, and accessibility of market-relevant information facilitated more understanding of market behavior among financial economists and market analysts. In turn, these developments provided a better factual and analytical foundation for journalists in their efforts to parse the often-complex drivers of stock markets for their readers.

In short, information about economic activity and corporate performance deepened and densified over time, leading to more understanding of the forces that trigger stock market jumps. Thus, we hypothesize that jump clarity has trended upward over the long sweep of our US sample. We assess this hypothesis in Figure 10, which plots the yearly average value of our Clarity Index and each of its components from 1900 to 2022. (There are no US jumps in 2023.) The average index value fluctuates a great deal from year to year, but there is a clear upward trend from the 1920s through the 2010s on the order of 1.5 standard deviation units. All four index components also exhibit large upward trends, with some differences in timing. Neither the Clarity Index nor any of its components show a clear trend before the 1930s, which fits with the timing of major advances in the volume, quality, and accessibility of market-relevant information. Figure A11 presents an analogous set of time-series plots for the United Kingdom from 1930 to 2020. The UK clarity data also exhibit an upward trend. In fact, the upward drift is even more pronounced in the UK data.

In summary, our analysis uncovers a clear upward trend in clarity about the reasons for stock market jumps over roughly the past century in the US and UK stock markets. To our knowledge, this is a new finding with no close antecedent in the literature. It says that stock market jumps have become less mysterious and more grounded in readily perceived news events over the past century. Given our earlier evidence that greater clarity leads to less market volatility, it also suggests that the upward drift in jump clarity is a force that works to dampen stock market volatility. Fluctuations in jump clarity, like those in stock market volatility, are positively autocorrelated (Table A7).

4.5 Clarity and the Geographic Origin of Market-Moving News

Finally, we ask how jump clarity relates to the geographic origin of market-moving news. For this question, it is important to consider a larger sample of countries. Two practical matters arise. First, because reads that designate the jump reason as Unknown & No Explanation have no geographic origin, we drop them. Second, when looking beyond the US and UK, we usually have only one read per jump and, hence, cannot compute pairwise agreement at the jump level. Thus, we now work with a Simplified Clarity measure derived from the (average) jump-level values for Ease of Coding and Journalist Confidence. We normalize Ease of Coding and Journalist Confidence values to mean zero and unit standard deviation by country, and we then sum these two values at the jump level and again normalize to mean zero and unit standard deviation at the country level.

Table A8 reports jump-level regressions of Simplified Clarity on Foreign, which equals 1 if the geographic origin field contains the home country only, ½ if it contains the home country and another country (or region), and 0 otherwise. We again control for jump size, jump direction and market volatility over the prior day, week and month in the regressions. Using US data from 1900 to 2022, we find that Simplified Clarity is 0.63 (0.18) standard deviation units greater for jumps attributed to news about developments in other countries. When we pool jumps over all 19 countries from 1980 to 2020, we find that Simplified Clarity is 0.29 (0.05) standard deviation units greater for jumps triggered by developments originating in other countries. Thus, there is compelling evidence that jumps attributed to foreign developments are associated with greater clarity.

5. Concluding Remarks

We examine next-day newspaper accounts of large daily jumps in 19 national stock markets to assess their proximate cause, clarity as to cause, and the geographic source of the market-moving news. Our sample of over 8,000 jumps reaches back to 1900 for the United States and 1930 for the United Kingdom. News about the macroeconomy and its outlook accounts for one-quarter to one-third of the jumps in our sample, depending on period and country. The next-most common category is news about corporate earnings, followed by news about monetary policy and government spending. Sovereign military actions are a prominent source of jumps in the first half of the 20th century, especially during World Wars I and II. Journalists offer no explanation for about one-tenth of the jumps since 1980 and a much higher share in the first half of the 20th century. News about the United States exerts an extraordinary influence on national stock markets around the world.

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. Even more striking, upward jumps due to monetary policy and government spending occur with much greater frequency after a crash in the national stock market. This pattern holds for the United States and in a broader sample of seventeen countries. Our UK and US results for the period since 1980 imply that a 20 percent stock market drop raises the likelihood of an upward jump due to monetary policy or government spending by a factor that is roughly ten times as large as the unconditional likelihood of any jump attributed to monetary policy or government spending. Thus, the so-called "Fed put" is but one manifestation of a broader phenomenon that extends to fiscal policy and operates across many countries. This type of "policy put" pattern emerged long before the 1990s in the US and UK and has become more pronounced over time.

We also show that stock market jumps have become more grounded in readily perceived news events over the past century. We attribute this development to more transparency about corporate performance, better statistical information about the economy, falling communication and information processing costs, and better financial news reporting. Greater clarity about the jump reason, as contemporaneously perceived, foreshadows less dispersion in firm-level equity returns. In a related finding, jumps attributed to monetary policy have high average clarity and foreshadow much less volatility than other jumps. This result suggests that jump-inducing monetary policy actions resolve uncertainties in a manner that tamps down stock market volatility, on average. Jumps attributed to other reasons don't share this property.

Our study points to several directions for new research. One is to more fully analyze the policy put phenomenon, which prior research attributes mainly to Fed behavior since the 1990s. Our evidence points to a broader role for deliberate, often successful, policymaker efforts to engineer countercyclical shocks in the wake of stock market crashes. How is it that monetary and fiscal authorities manufacture upward stock market jumps twice as often as downward ones? And 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 what is 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 is opposite to the pattern we find for stock market jumps triggered by monetary policy and government spending.

It would also be useful to more fully explore the determinants and consequences of clarity about the forces that drive stock market jumps. In this respect, our measurement approach opens the door to new studies of how the accuracy, depth, and timeliness of economic statistics affect clarity about stock market behavior. How does greater clarity about stock market drivers influence overall market volatility? How much does it matter for economic performance? What is the social value of the statistical improvements that contribute to greater clarity about stock market behavior?

Another natural direction for future research is to disentangle the roles of discount rate shocks and news about future cash flows in stock market jumps. While central to asset pricing models, this distinction is often muddled in newspaper accounts. Thus, 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) and the more data-intensive approaches of Knox and Vissing-Jorgenson (2024) and Nagel and Xu (2024), for example.

Yet another direction is the use of automated approaches to classify and characterize jumps, drawing on tools from natural language processing and machine learning. We have made efforts in this direction with limited success. A basic challenge is 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. Thin samples in this respect undercut the feasibility of the train-test-refine protocol typical of supervised machine-learning methods. While frontier language models have achieved some success in zero-shot or few-shot classification tasks in some settings, they are not yet capable of executing the highly granular and nuanced distinctions that we set forth in our coding guide and implement via human readings. Still, we recognize that text-analytic methods and 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.

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Appendix

The appendix figures and tables report additional results referenced in the main text. In most cases, the construction of these tables and figures is described in the main text or the notes to the relevant figures and tables.

Industry-level Validation Exercise

The industry-level returns validation exercise reported in Table A2 requires a more extended explanation, which we now provide. For some daily stock market jumps, the explanation offered in next-day newspaper accounts implies an amplified or dampened response of equity returns in particular industries to the news that moved the overall market. Consider two examples, the first involving bank stocks and the second involving defense-industry stocks

- Example 1, Banks: During the GFC, the stock market responded positively to upward revisions in the likelihood or generosity of bank bailouts. For this type of jump, we expect an even more favorable response for Bank stocks. That is, the response of Banks is ***amplified*** relative to the overall market response.
- Example 2, Guns: When bad news about the likelihood or duration of the Iraq war generated a negative jump, we expect the response for Guns (defense firms) to be ***dampened*** relative to the overall market response. While a longer war may be bad for the overall US economy, it is less bad (or even good) for Guns.

These examples suggest that we can test whether newspaper-based explanations are accurate by examining whether their implications for relative industry-level returns hold in the data.

To do so, we proceed as follows. First, let R_{it} = the daily return for industry portfolio *i* on day *t* as measured by Fama and French (2023). Second, we use the detailed explanations offered in next-day newspaper accounts – as recorded by our human readers – to identify instances in which particular industries should have an amplified or dampened return response if the newspaper explanation is accurate. Using these detailed explanations, we construct an industry-level variable Tri_{it} that takes on three possible values for each industry *i* on each jump date *t,* as follows:

Tri_{it} = 1, if the detailed description for *t* implies an amplified response of R_{it};

= -1, if the detailed description for *t* implies a dampened response of R_{it};

= 0, otherwise.

In constructing this variable, we take a conservative approach: We set Tri to 1 or -1 based on the Primary jump reason only. We set Tri to 0 when the detailed explanation for the jump involves an overly broad industry group. For example, "Manufacturing" maps to at least 15 of the 49 industry groups and is too broad for our purposes.[21]

Most jump-day explanations do not map readily to a particular industry. Sometimes, we assign 2 industries to a given jump. Most, but not all, of these dual assignments involve Sovereign Military Jumps, which implicate both Guns and Aerospace. Among our 339 jumps from 1960 to 2016, we obtain 115 Jump-by-Industry observations with nonzero Tri values, as follows: 38 nonzero values for Banks, 19 for Guns, and 16 for Aerospace. Several other industries had fewer than 10 nonzero Tri values: Oil, Coal, Building Materials, Construction, Autos, Chips, Hardware, Household Goods, Software, and Electrical Equipment.

Third, we test whether the implications of newspaper accuracy for relative industry-level returns hold in the data. In our one-industry-at-time approach, we fit the following regression model by OLS to daily returns data for a given industry *i,*

$$R_{it} = \alpha + \beta MR_t + \delta Tri_{it} + \gamma Tri_{it} MR_t + \epsilon_t,$$

where $MR_t =$ the daily return on the overall market portfolio on day *t.* The chief coefficient of interest is γ, which tells us whether the relative industry-i return is amplified or dampened on particular jump days. The null hypothesis is $\gamma = 0$. Newspaper accuracy implies the alternative hypothesis, $\gamma > 0$. The specification includes a control for the market return, because industry *i* may be relatively sensitive or insensitive to market returns for reasons apart from the ones identified in our newspaper explanations on jump days.

We report the estimated γ coefficient in this regression for the Banks industry in columns (1) and (2) of Table A2. We soundly reject the null hypothesis in favor of the alternative, as seen by the positive sign and statistical significance of the γ coefficient. The estimated value for γ in Column (1), for example, says the return for Banks is amplified by 80 percent relative to the average market return on jump days with $Tri_{Banks} = 1$. Thus, the results in Columns (1) and (2) strongly support the view that next-day newspaper explanations are accurate as to the reason for the jump – at least for those jump explanations that imply an amplified response for Banks.

[21] In practice, *Tri* typically takes on only two values (0 and 1, or 0 and -1) for a given industry. However, when pooling over industries to get additional power in the regression test below, we will need the trichotomous variable.

As it turns out, Banks is the only industry with a large enough number of non-zero *Tri* values to yield reasonably precise estimates of γ. Thus, we also fit a multi-industry regression specification, as follows:

$$R_{it} = \sum_i \alpha_i + \sum_i \beta_i MR_t + \sum_i \delta_i Tri_{it} + \gamma Tri_{it} MR_t + \epsilon_t.$$

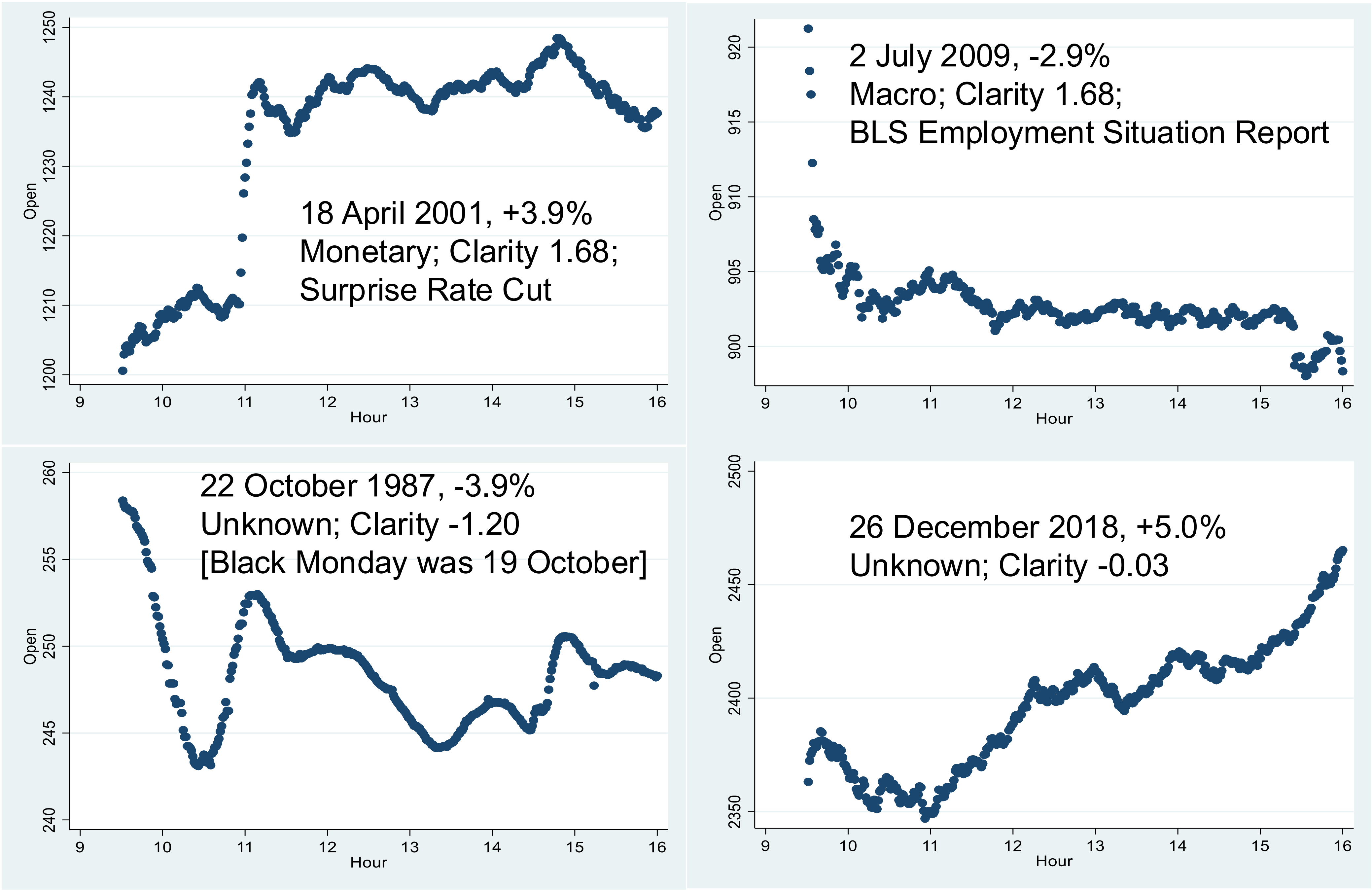
When fitting this regression, we pool over all industries with at least one nonzero *Tri* value. Columns (3) and (4) in Table A2 report the results. Again, we soundly reject the null hypothesis in favor of the alternative, and the estimated value for γ implies a large amplification/dampening effect on returns in those industries that, according to the newspaper-based explanation, should experience an amplification/dampening effect.

In summary, the results in Table A2 provide evidence that next-day newspaper accounts contain meaningful explanations for large daily moves in national stock markets. This evidence about industry-level returns on jump days complements the evidence in Table 3 discussed in the main text. In particular, we stress that Table 3 and Table A2 provide two distinct types of evidence that validate our newspaper-based classifications for jump reasons, and the newspaper explanations themselves.

Comparison to Cutler, Poterba and Summers (1988)

Cutler et al. (1988) consider the 50 largest daily US stock market jumps from 1946 to 1987 and attribute a cause to each one based on coverage in the *New York Times*. For these 50 jumps, we map their assigned cause to a primary jump-by-reason category (and sometimes a secondary one as well), using our granular categories in Table 1. Their primary reason agrees with our primary reason for 65 percent of the 50 jumps. When we allow for agreement on primary or secondary reasons, we obtain a 72 percent agreement rate. See the bottom row in Appendix Table A9. When we focus on jumps with above-average clarity values, according to our clarity metric, we obtain an 80 percent agreement rate for primary reason (and an 88 percent agreement rate for primary or secondary reasons). Given the differences in methodologies and author teams, and the granular nature of our jump-by-reason classification, we are reassured by these agreement rates. At the same time, it’s noteworthy that we find much smaller agreement rates for Low Clarity Jumps, reinforcing the conclusion that it’s hard to confidently discern the reason for some stock market jumps.

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

352

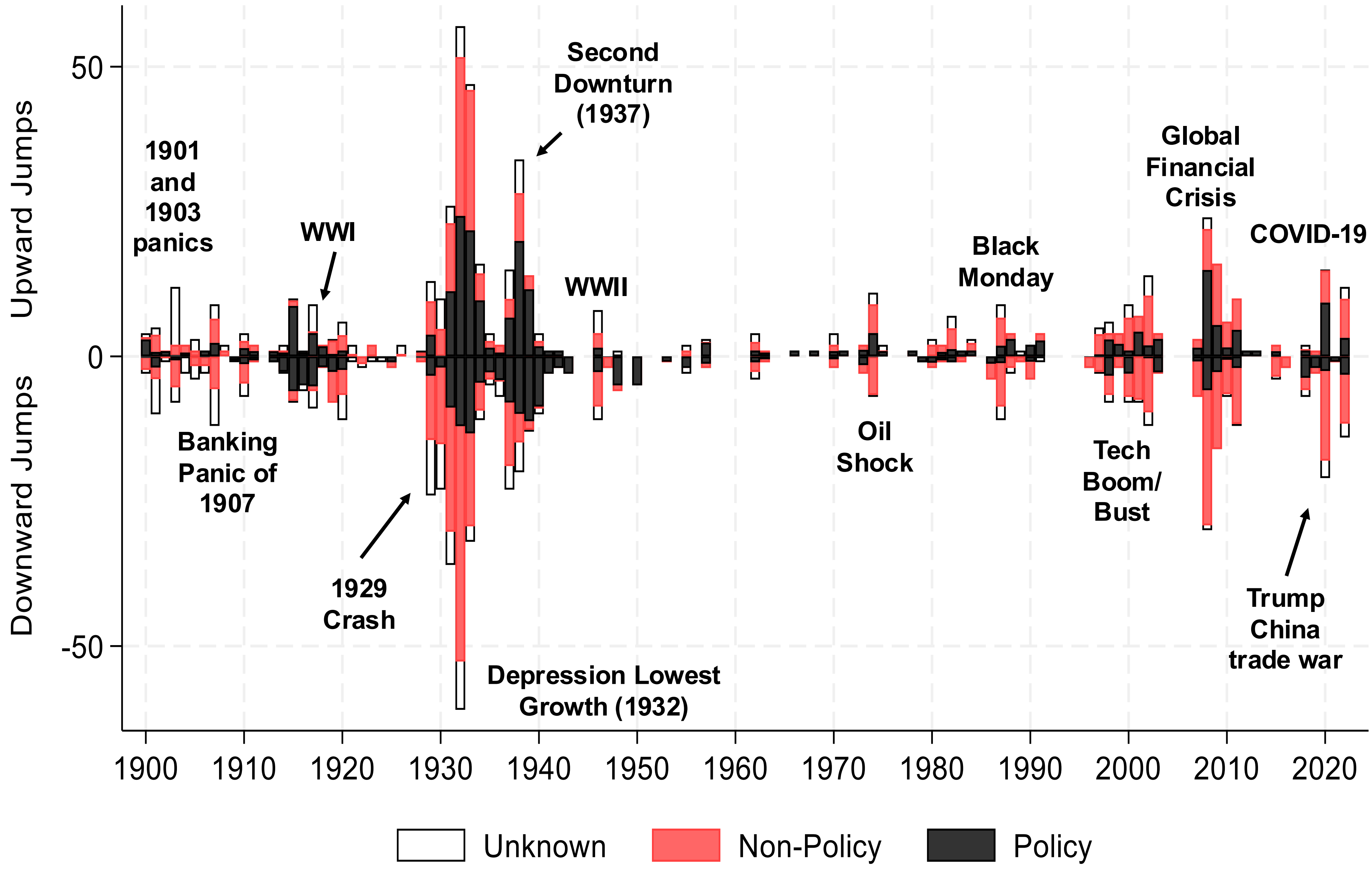
Throughout Wall Street's December meltdown, analysts have been saying that markets were plunging despite plenty of evidence that the United States economy remains strong and corporate profit growth is healthy.

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.

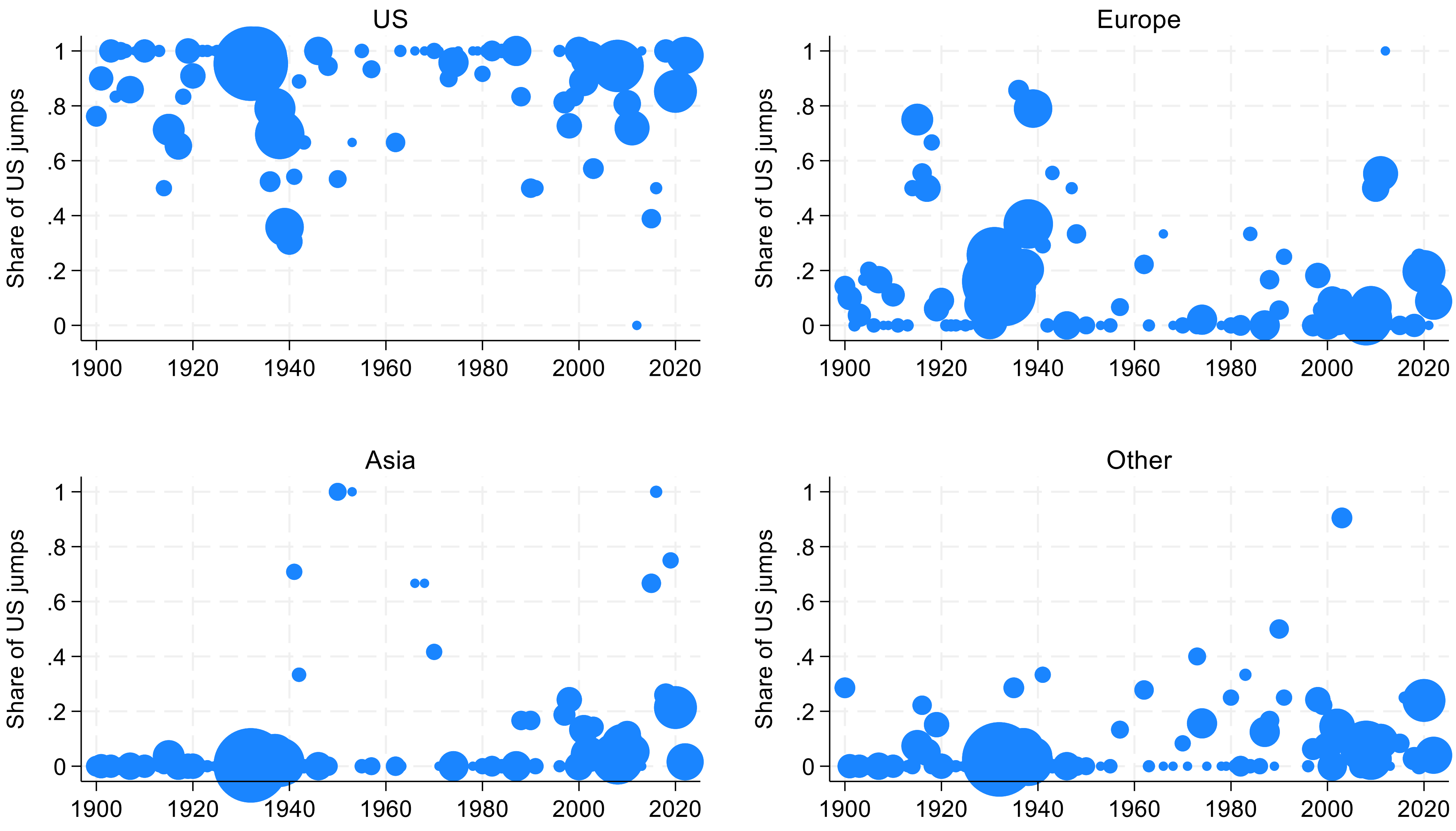
For the NY Times article at right, we code the primary jump reason as **Macro News and Outlook,** because the article attributes the jump mainly to good news about consumer spending. Geographic source is the **US**. Journalist confidence and ease of coding are both **Medium.**

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



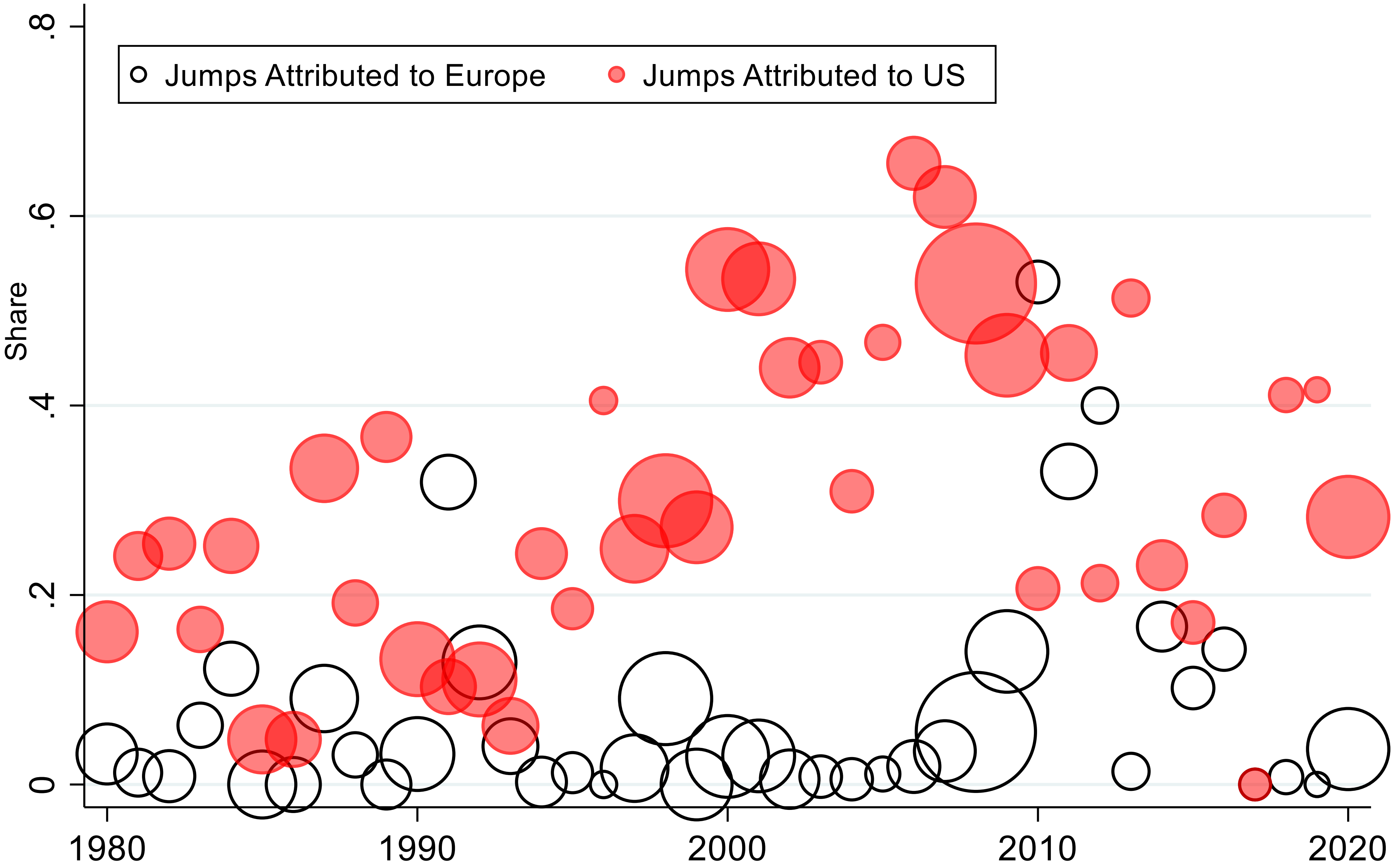
Notes: Each bar is the number of positive or negative jumps in that year. Black and red shadings indicate jumps triggered by "Policy" and "Non-Policy" developments, respectively. The unshaded parts of each bar reflect jumps coded as "Unknown or "No Explanation Offered" plus five instances before 1926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

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



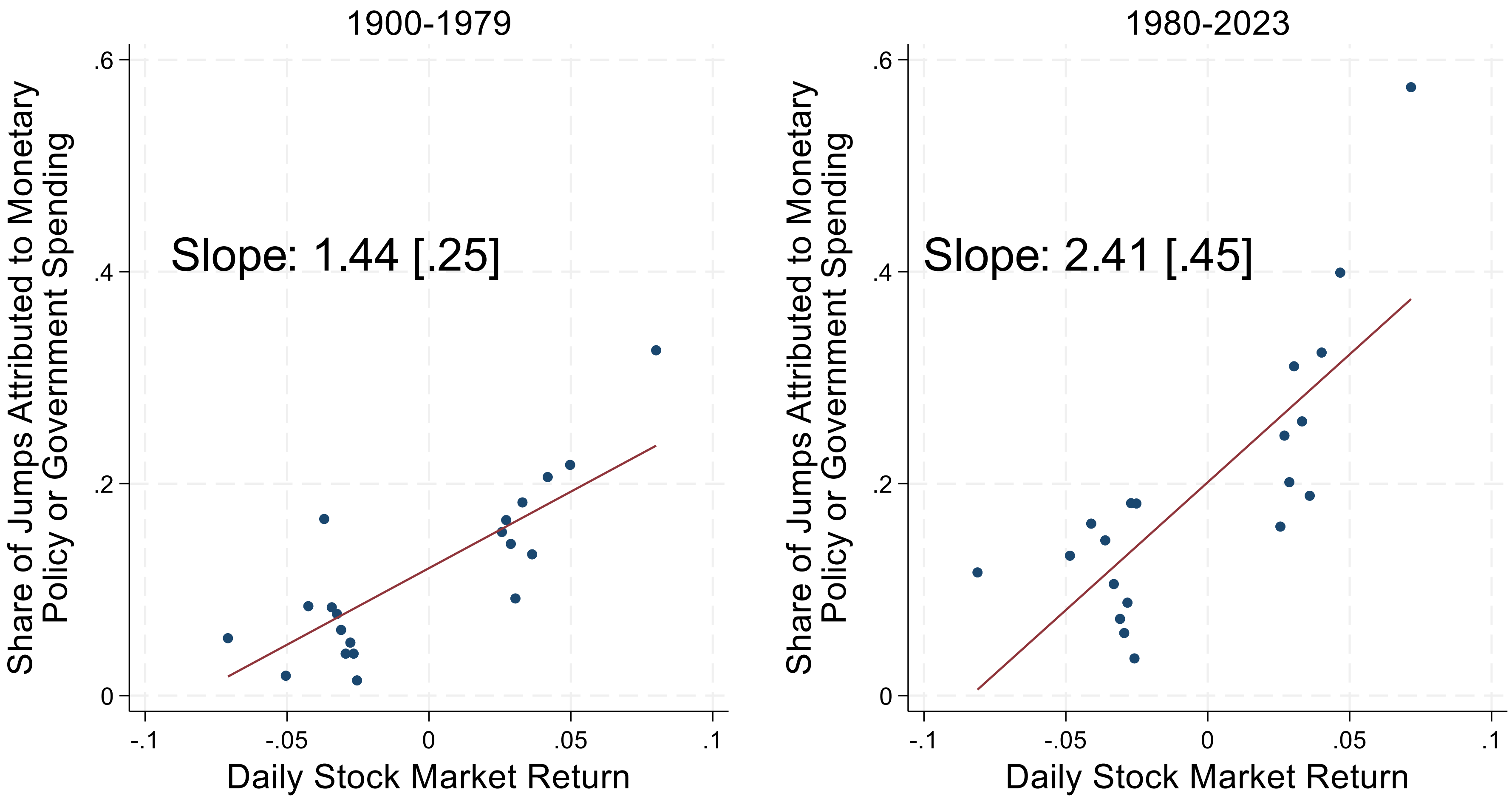
Notes: Dots show the yearly share of U.S. stock market jumps by the geographic origin stated at the top of the panel. Dot size reflects the number of jumps in that year. This chart excludes jumps classified as “Unknown or No Explanation Offered” and “No Article Found,” which have no geographic attribution. 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 <u>other</u> 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.

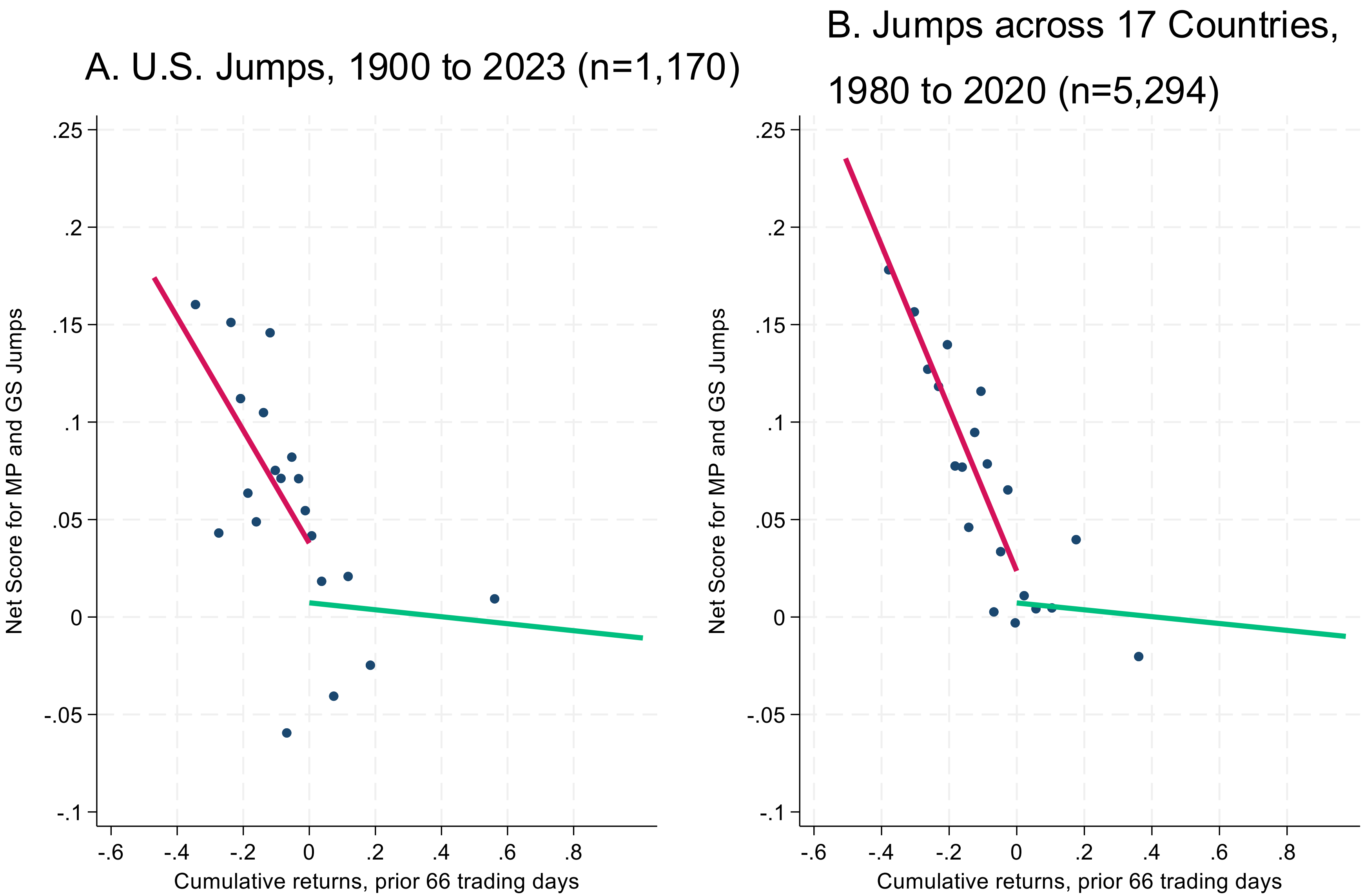
Figure 7: Monetary Policy and Government Spending Trigger A Larger Share of Upward than Downward Jumps in the U.S. Stock Market, More So After 1980



Difference in slopes: 0.97, t-stat: 1.90

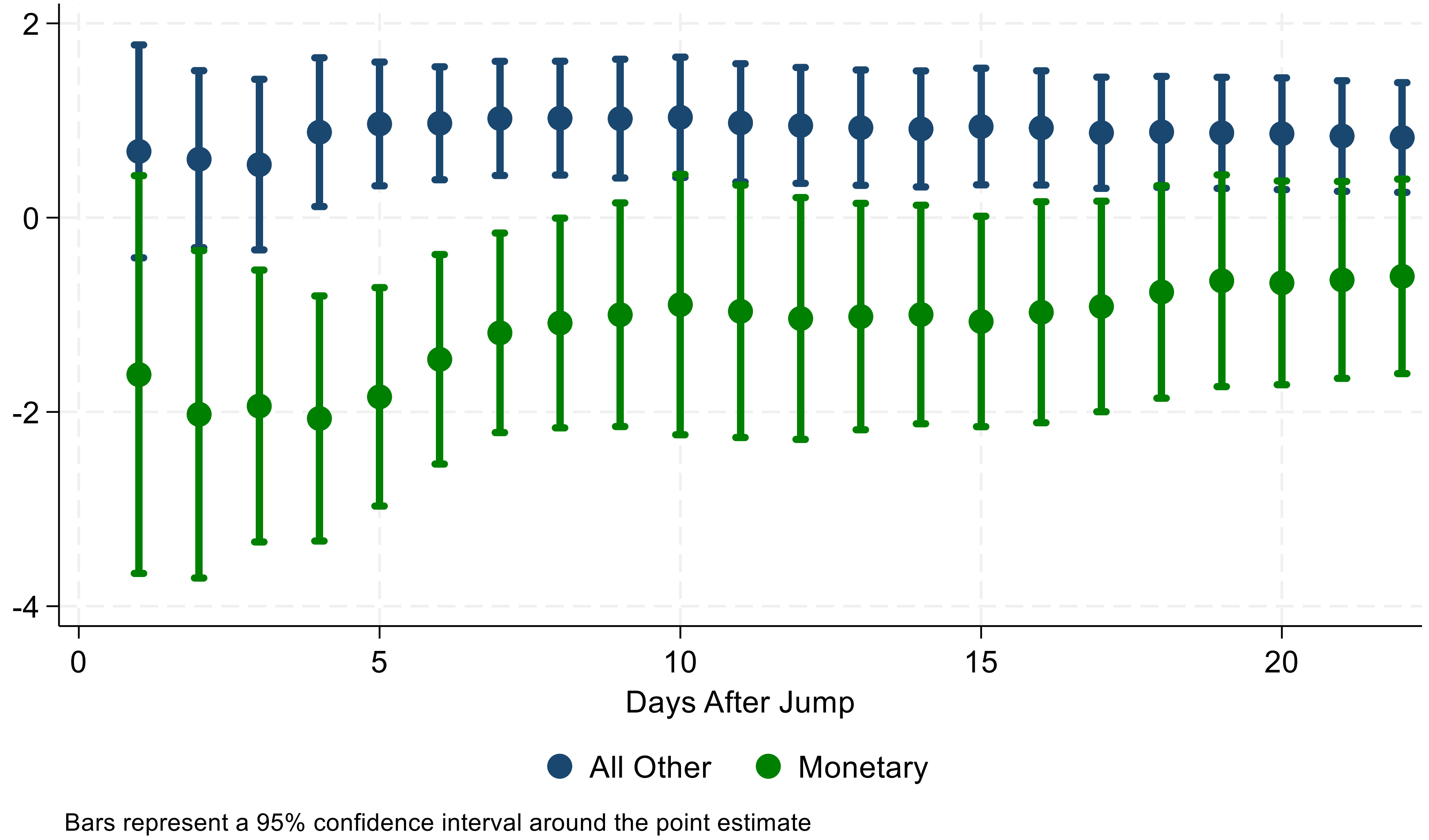
Notes: Each panel shows a bin scatter (n=20) of $MP_t + \mathrm{GS_t}$ on jump-day returns, where MP_t is the fraction of the jump's codings attributed to Monetary Policy & Central Banking, and GS_t is the fraction attributed to Government Spending. We obtain the fitted line in each panel by regressing $MP_t + \mathrm{GS_t}$ 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.

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



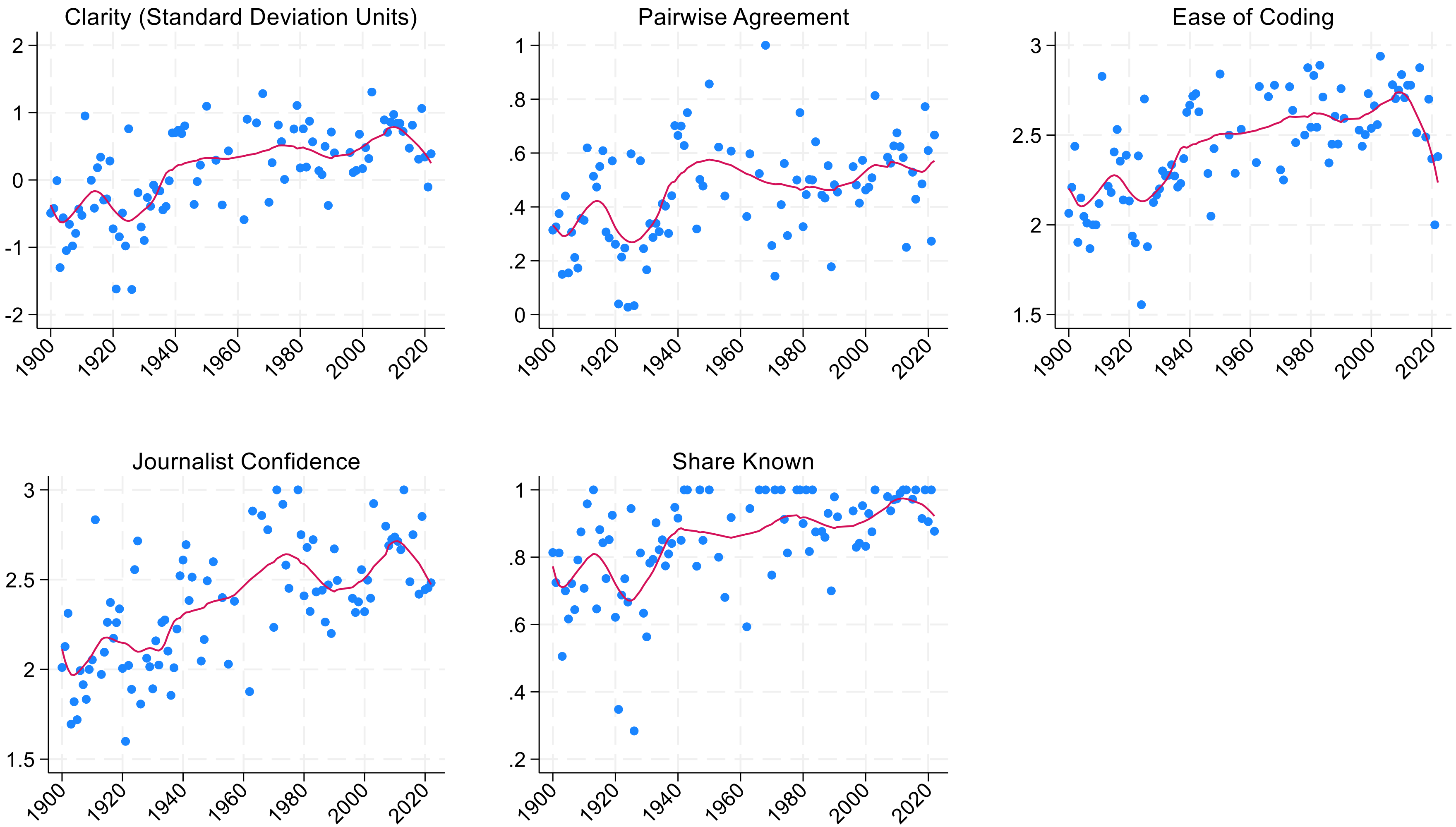
Notes: These charts show bin scatters of jump-level $NET(MP_t + GS_t)$ values on own-country market returns over the prior 66 trading days. $NET(MP_t + GS_t)$ equals the share of codings attributed to monetary policy or government spending for upward jumps and (-1) times that share for downward jumps. 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.

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



Notes: We regress average squared returns (volatility) over the *n* trading days after a jump day on the fraction of codings that attribute the jump to Monetary Policy and the fraction that attribute it to All Other reasons. We run a separate regression for each n=1,2,…,22 and in each case control for jump-day return, split into positive and negative pieces, and volatility over the day, week and month preceding the jump day (HAR controls). The chart plots coefficients on the two jump-type measures and 95% confidence intervals computed using Newey-West standard errors with lags set to 1.5 times *n.* The time-series standard deviations of average volatility over 1, 5, 10 and 20 days are 5.08, 3.20, 2.78 and 2.43, respectively. The difference between the coefficient on jumps attributed to Monetary Policy and the coefficient on those attributed to All Other reasons is statistically significant at the 1% level for all n>1. The marginal significance level for n=1 is 0.06.

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."

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

Notes: This table reflects human codings of articles in the *Wall Street Journal* for the United States, the *Financial Times* for the United Kingdom, and leading own-country papers for the other 17 national markets. See Table A1 for daily jump thresholds for equities and the exact sample period for countries in the Rest of the World (ROTW). The threshold for daily US bond jumps is a change of more than 15 basis points in the yield on 10-year U.S. Treasury securities.

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.

Table 4: The Put-Like Character of Jumps Triggered by Monetary Policy and Government Spending

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

A. U.S. Sample, 1990 to 2023	Gov. Spend + Monetary Jump Days	Gov. Spend + Monetary All Days	Government Spending Jump Days	Government Spending All Days	Monetary Policy Jump Days	Monetary Policy 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

B. 17-Country Sample, 1980 to 2020	Gov. Spend + Monetary Jump Days	Gov. Spend + Monetary All Days	Government Spending Jump Days	Government Spending All Days	Monetary Policy Jump Days	Monetary Policy 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

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

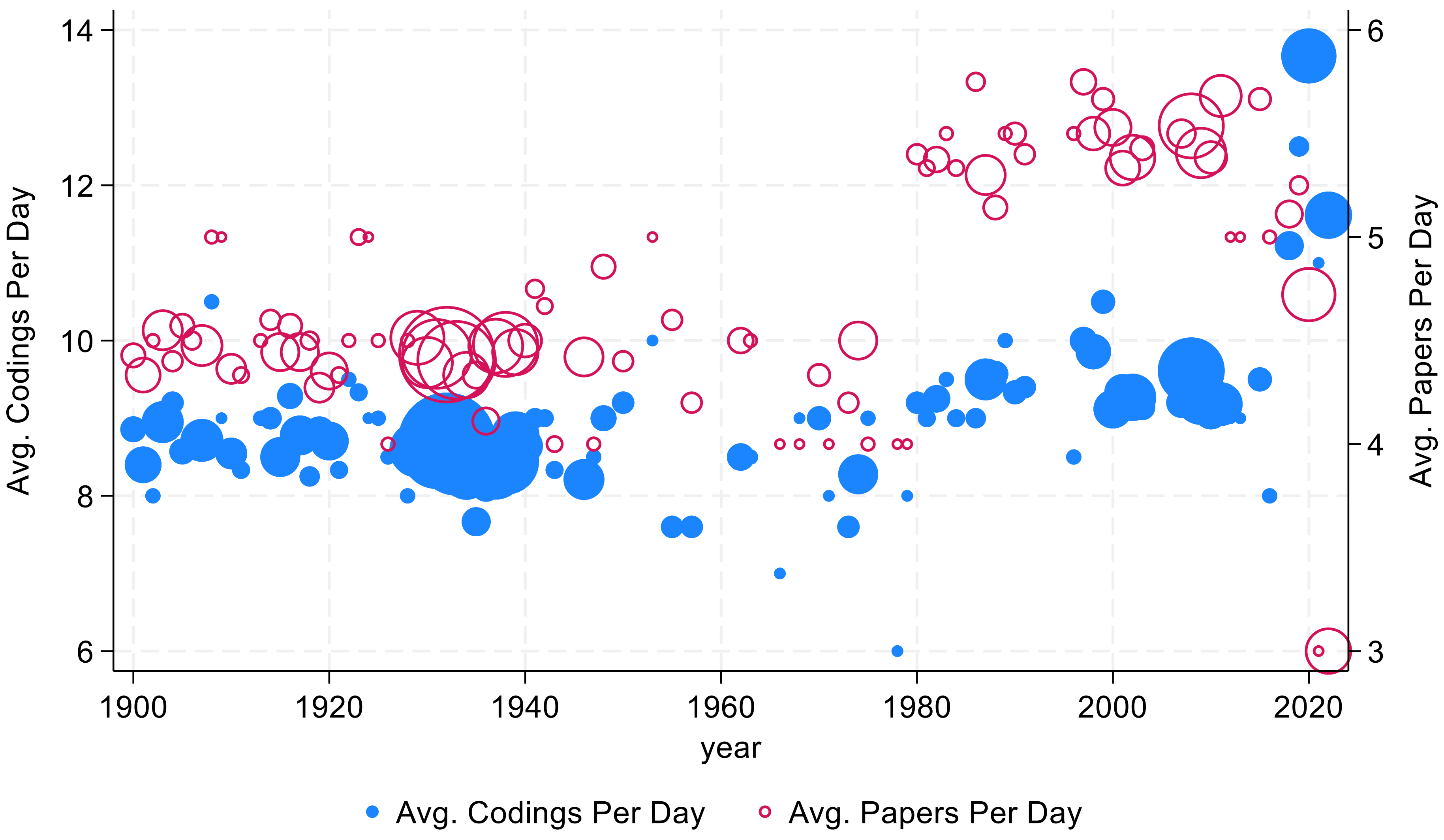
Notes: The dependent variable is the intra-day concentration of market-level returns on jump days, in defined in Section 4.2. Each column corresponds to a separate regression of intra-day concentration on our Clarity Index or one of its components. The Clarity Index and each component has mean zero and 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 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

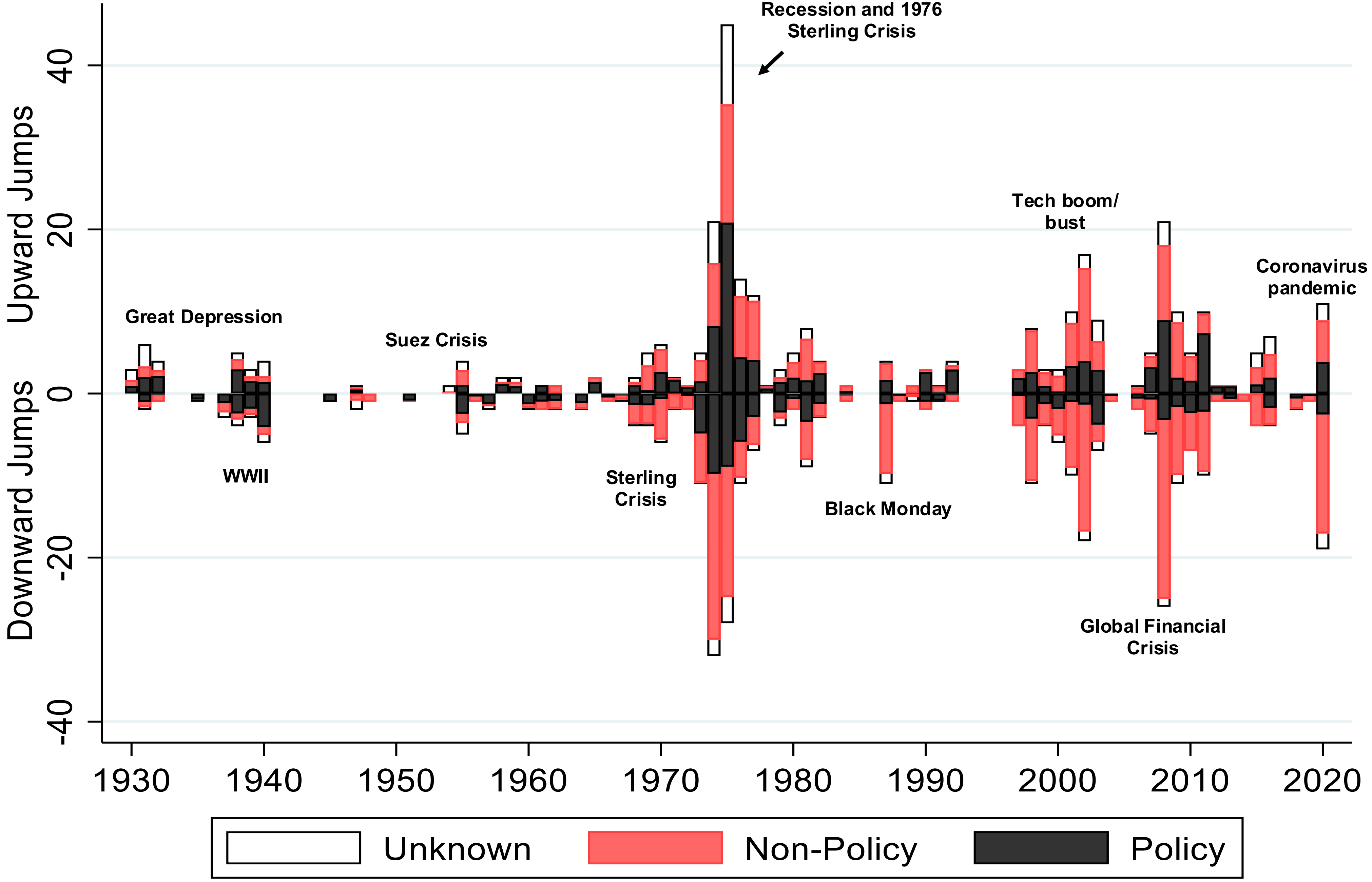
Notes: Each column reports a separate regression of the dependent variable on the Clarity Index. We compute the value-weighted cross-sectional standard deviation of firm-level returns using all ordinary common shares traded on major exchanges in CRSP. For columns 2 and 4, the controls are the jump-day 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

Figure A1: Average Number of Codings and Newspapers per Jump Day by Year for U.S. Stock Market Jumps, 1900 to 2023



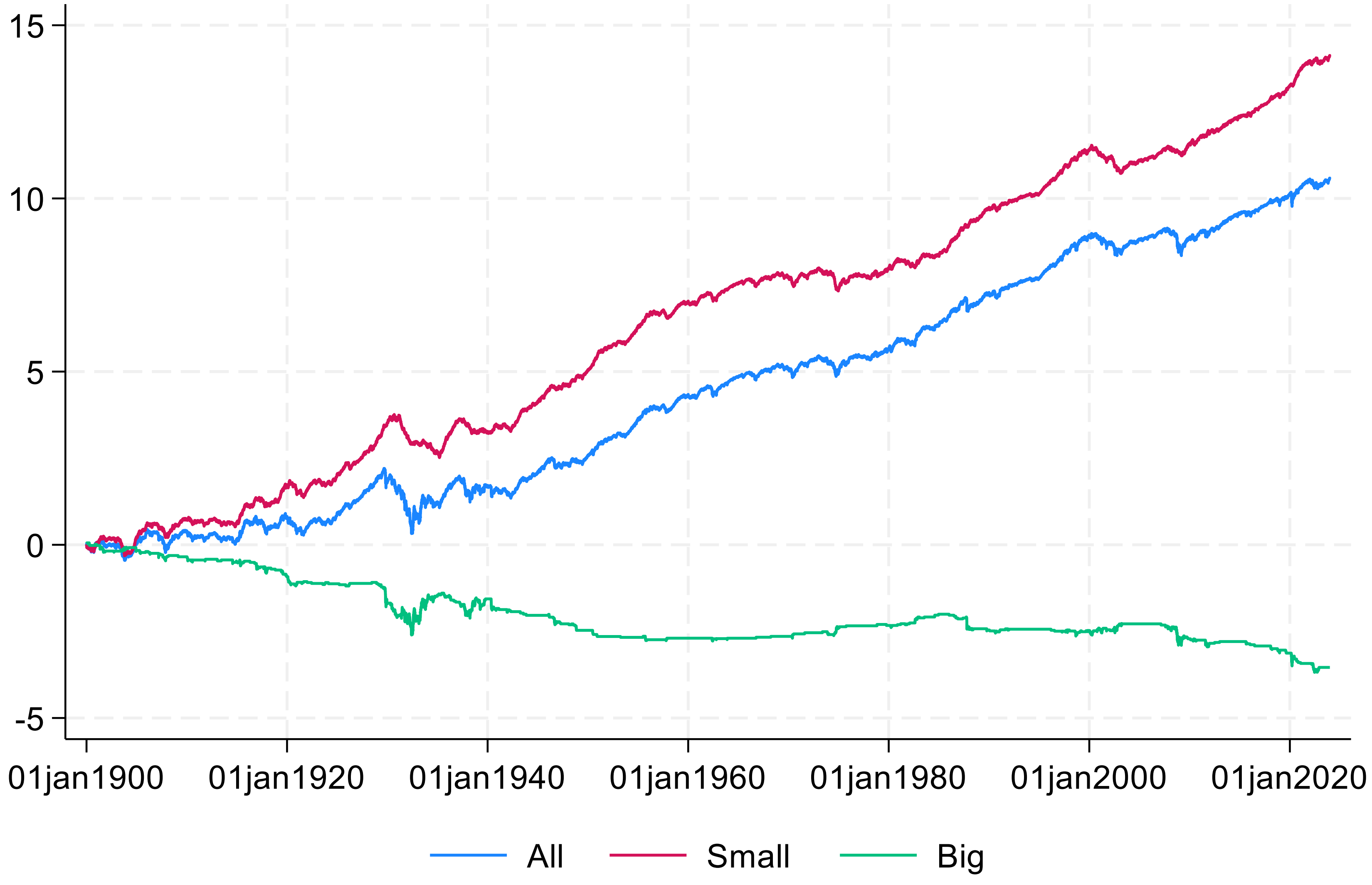
Notes: This chart shows average number of coders and newspaper per day, with the circle areas proportional to the number of jumps in that year. Data from 1900 to 2023.

Figure A2: UK Jumps by Year, 1930-2020



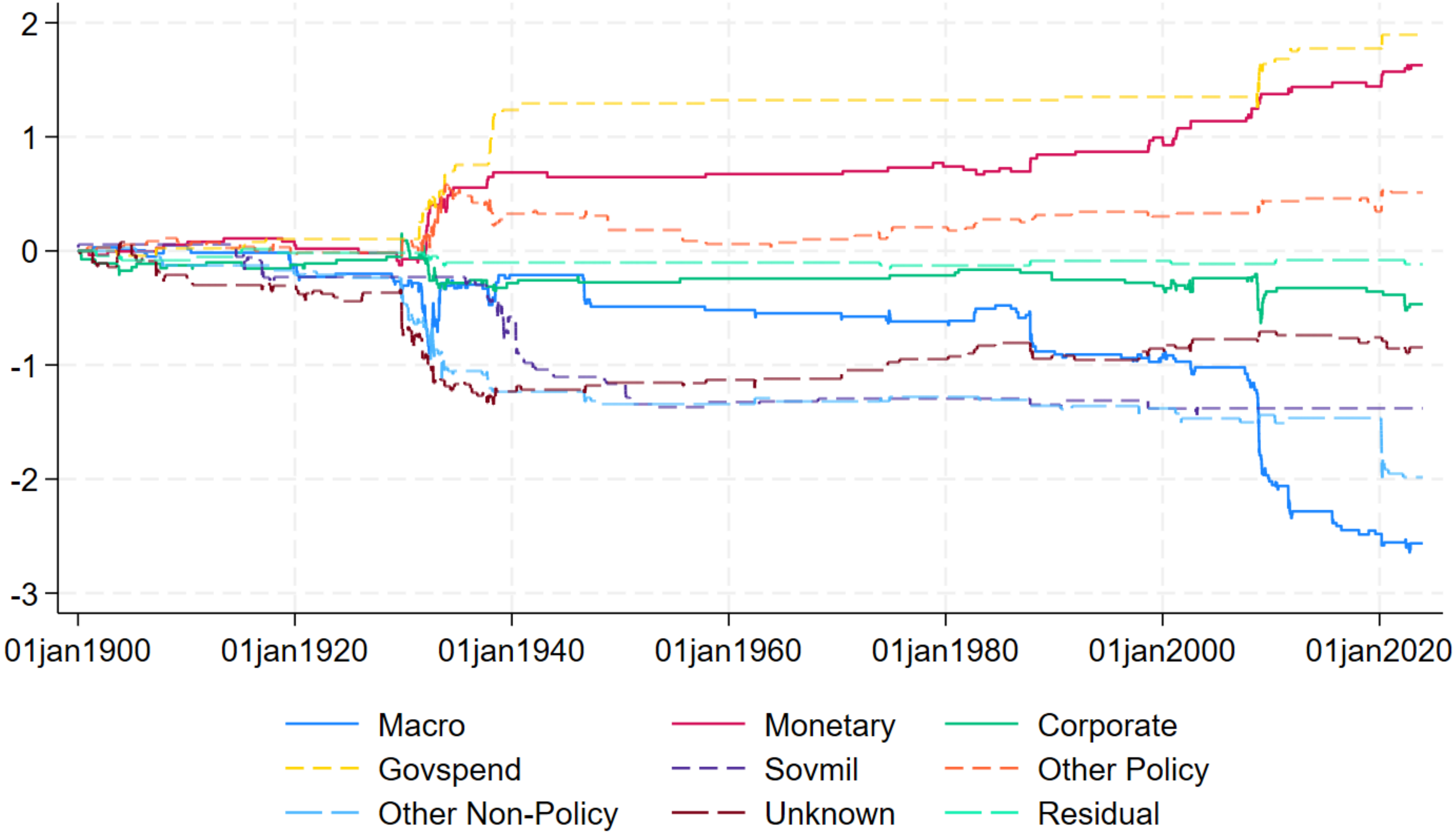
Notes: Each bar is the number of positive or negative jumps in that year. Shadings indicate the number of jumps triggered by "Policy", "Non-Policy" and "Unknown" news. Unknown includes "no article found". Data from 1930-2020.

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



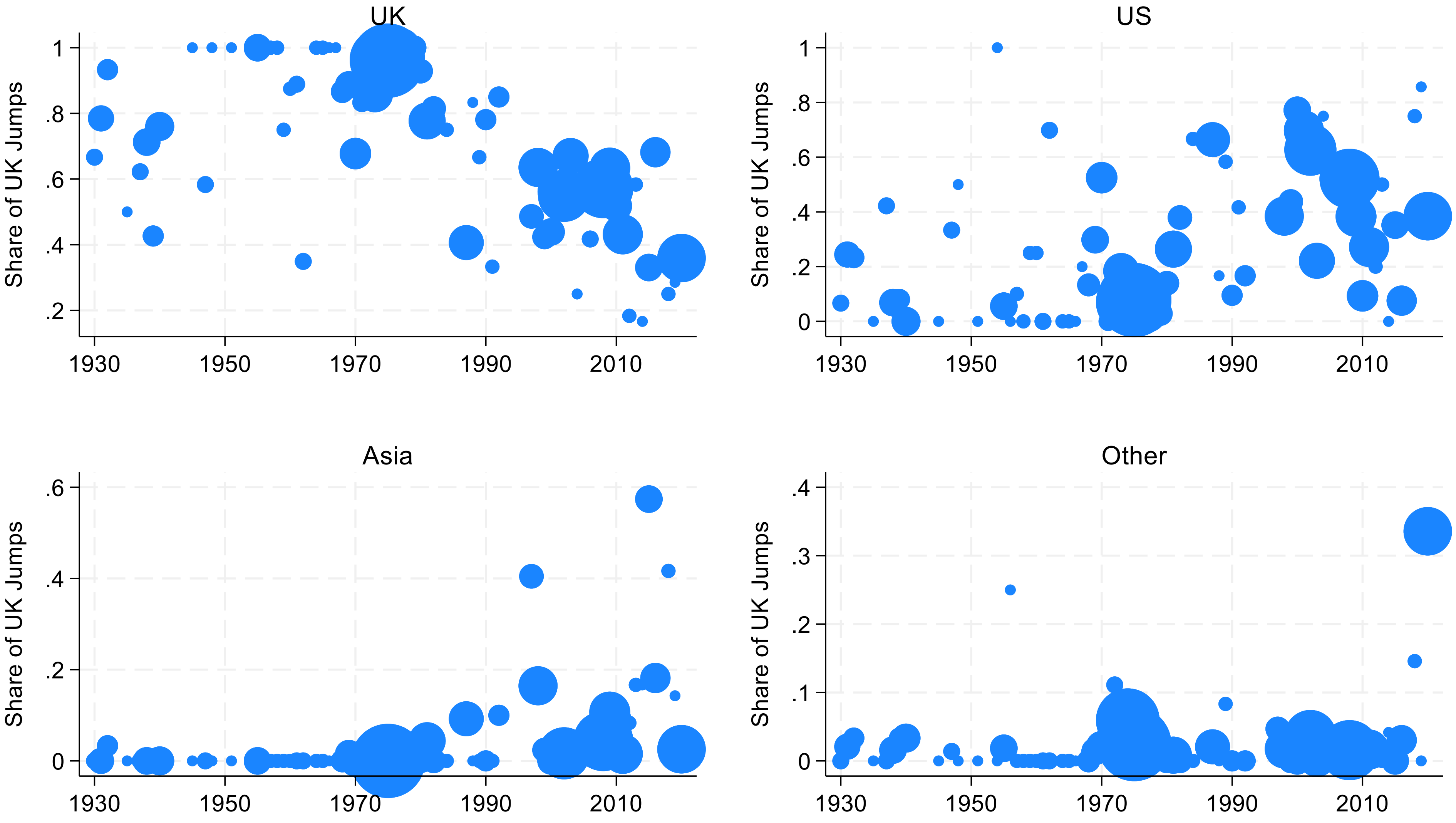
Notes: The blue curve shows the cumulative sum of daily log returns on the U.S. stock market from 2 January 1900 to 29 December 2023. The red curve shows the same measure restricted to trading days with “Small” moves (< |2.5%|), and the green curve shows the same measure restricted to jump days.

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



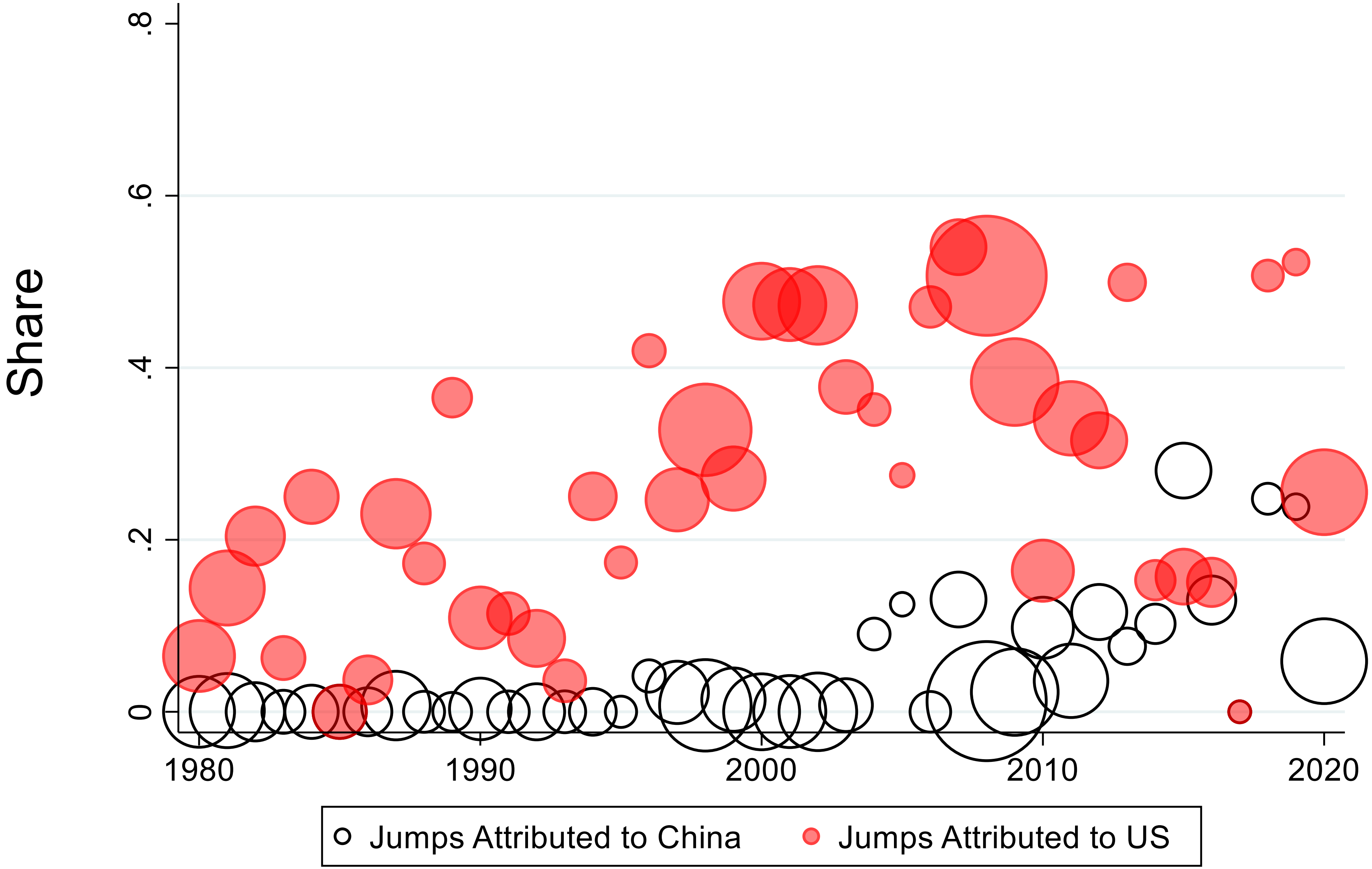
Notes: This chart plots the cumulative sum of daily log returns on the U.S. stock market from 2 January 1900 to 29 December 2023 for the indicated jump categories. The "Residual" plot covers all categories that are not listed explicitly.

Figure A4: Geographic Source of UK Jumps by Year, 1930-2020



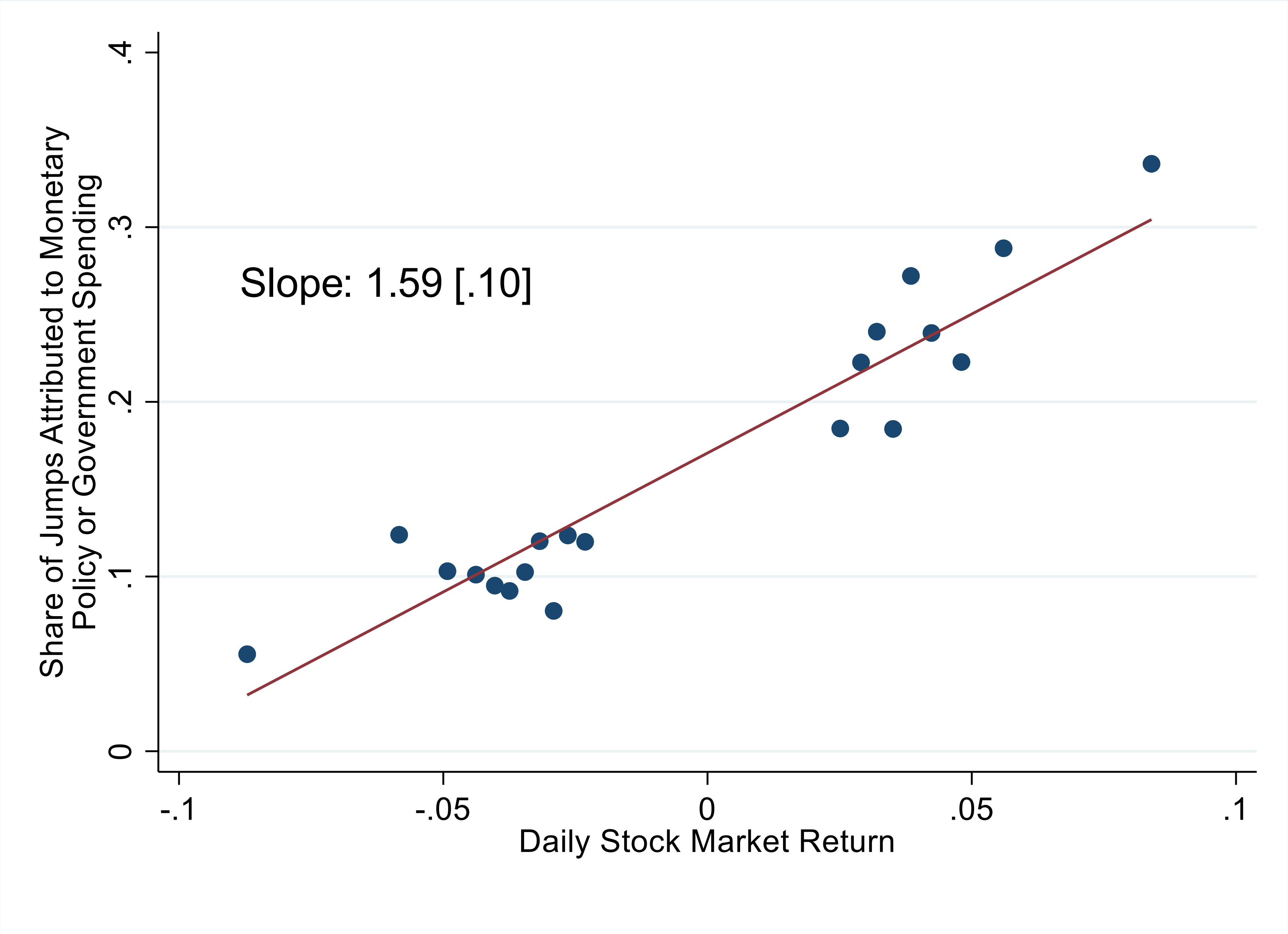
Notes: Dot shows the share of jumps in that year in the UK by their geographic origin. The size of the dots reflects the number of jumps in that year. Data from 1930 to 2020. Excludes unknown and no article found jumps, which have no geographic attribution.

Figure A5: News about China Triggers Few Jumps in the National Stock Markets of Other Countries before 2005 and a Sizable Share from 2010 Onwards



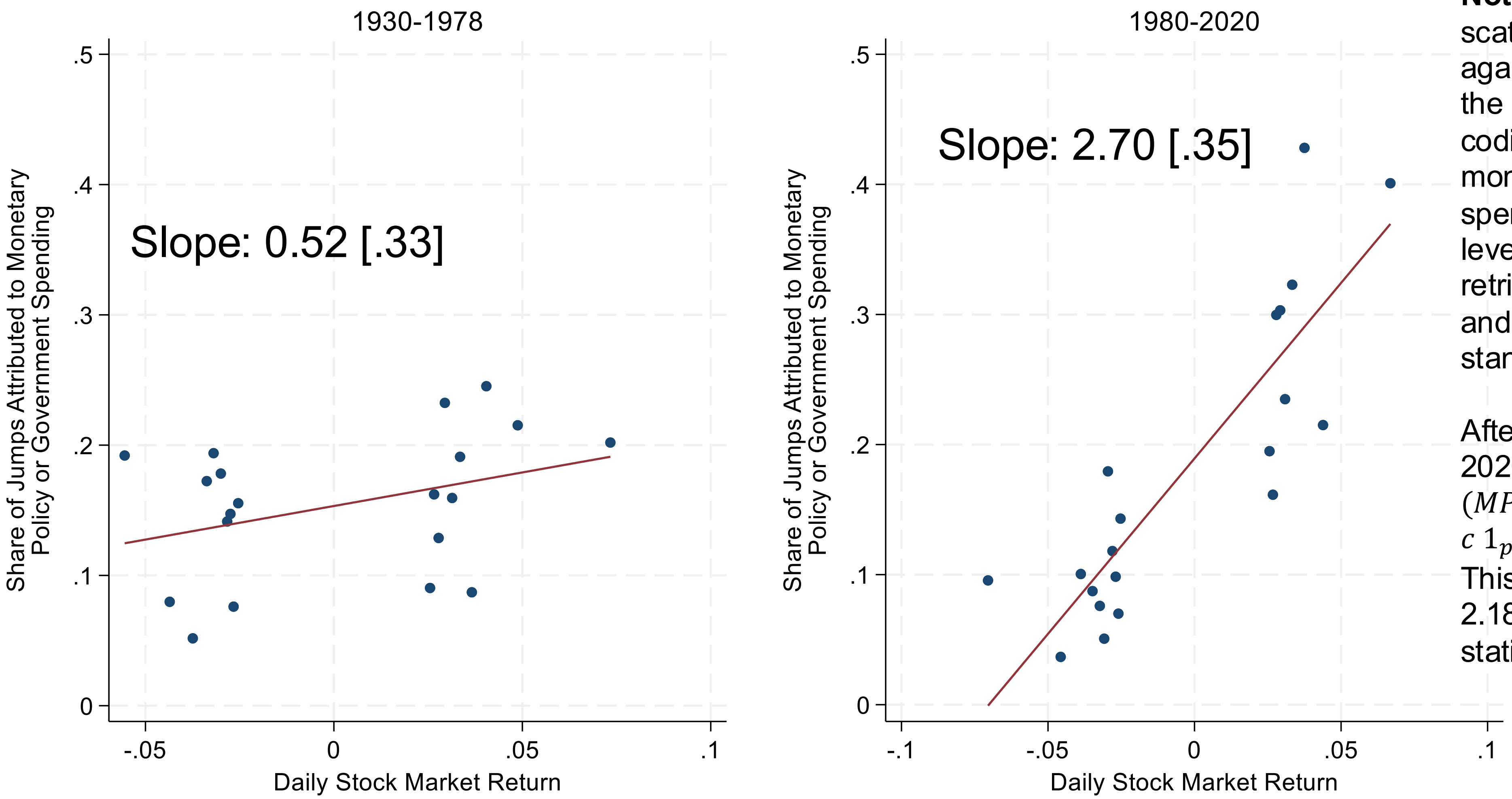
Notes: This figure shows the yearly share of daily jumps attributed to the US outside the US and the yearly share of daily jumps attributed to China outside of China and Hong Kong. The sample runs from 1980 to 2020 but does not cover all countries in all years. Dot size is proportional to the average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

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.

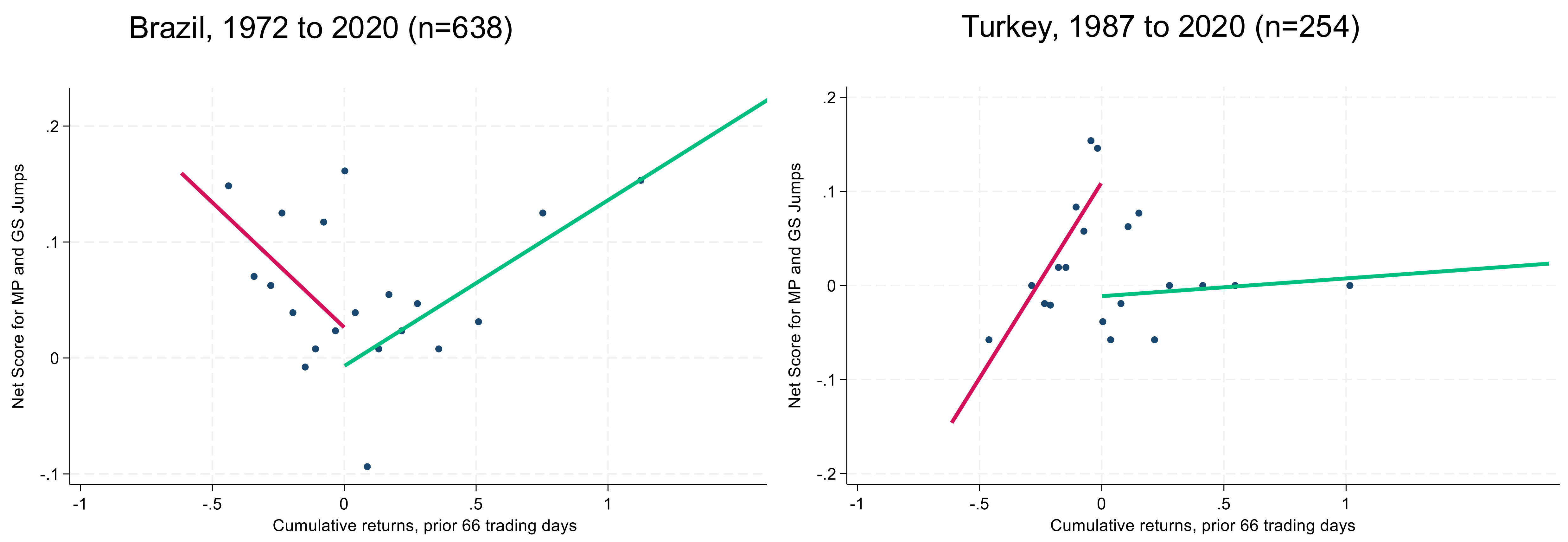
Figure A7: Monetary Policy and Government Spending News Triggers a Larger Share of Positive than Negative Jumps, Especially After 1980, in U.K. Data from 1930 to 2020



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.

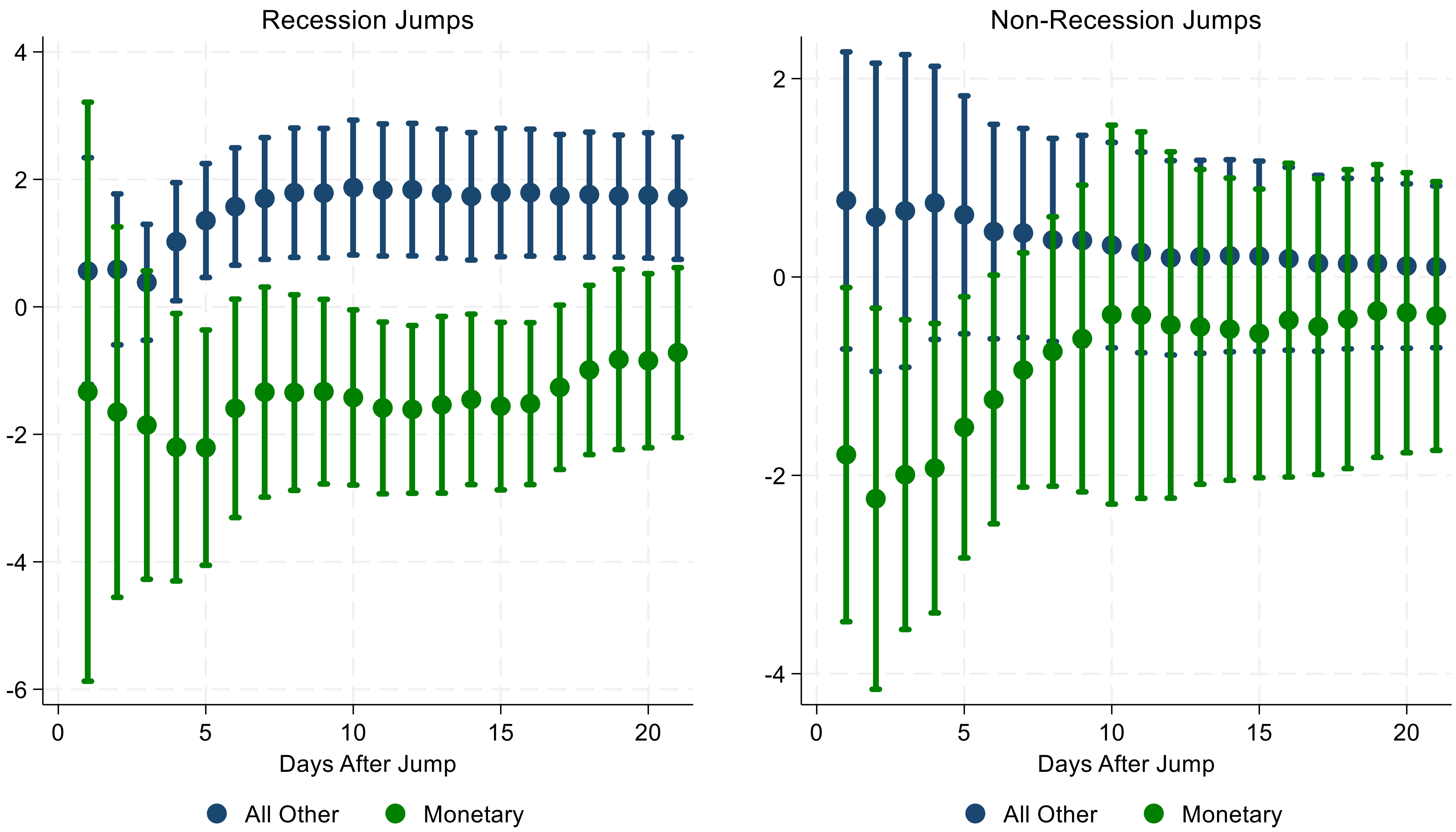
After pooling the data from 1930 to 2020, we run the following regression, $(MP_t + \mathrm{GS_t}) = a + b\, return_t + c\, 1_{post80} + d\, return_t \times 1_{post80} + e_{\mathrm{t}}$. This regression yields a coefficient of 2.18 on the interaction term with a t-statistic of 4.47.

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



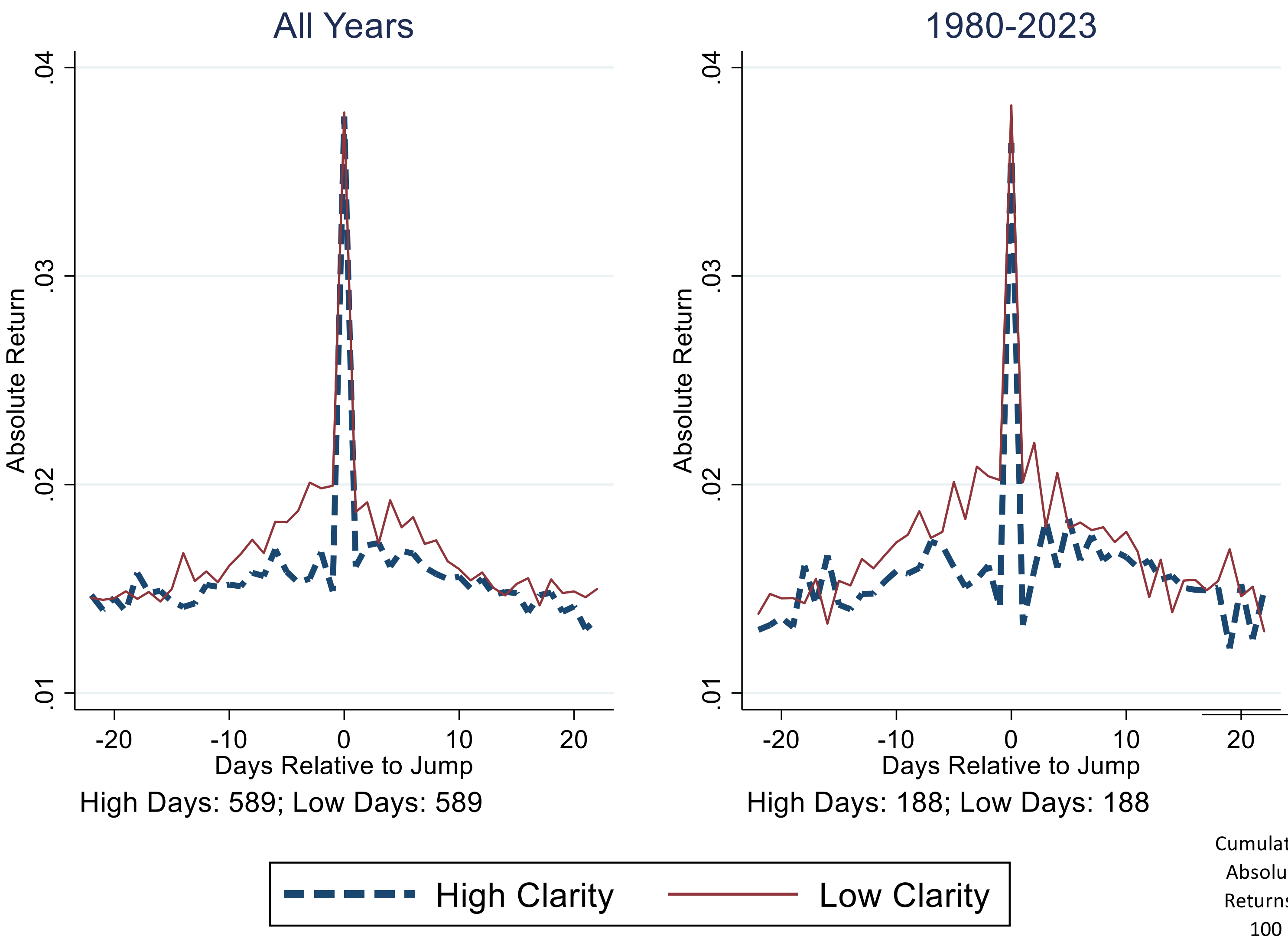
Notes: These charts show bin scatters of jump-level $NET(MP_t + GS_t)$ values on own-country market returns over the prior 66 trading days in Brazil and Turkey. $NET(MP_t + GS_t)$ equals the share of codings attributed to monetary policy or government spending for upward jumps and (-1) times that share 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.

Figure A9: Volatility after Jumps Attributed to Monetary Policy and All Other Categories Compared, Recessions versus Expansions, Daily U.S. Data from 1900 to 2023



Notes: This chart is based on the same data as Figure 9 in the main text. The regression specifications differ only in that we now allow the coefficients on "Monetary Policy" jumps and "All Other" jumps to differ between jumps that occur in NBER-dated recessions and those that occur in expansions. See the notes to Figure 9 and Section 3.6 for more information.

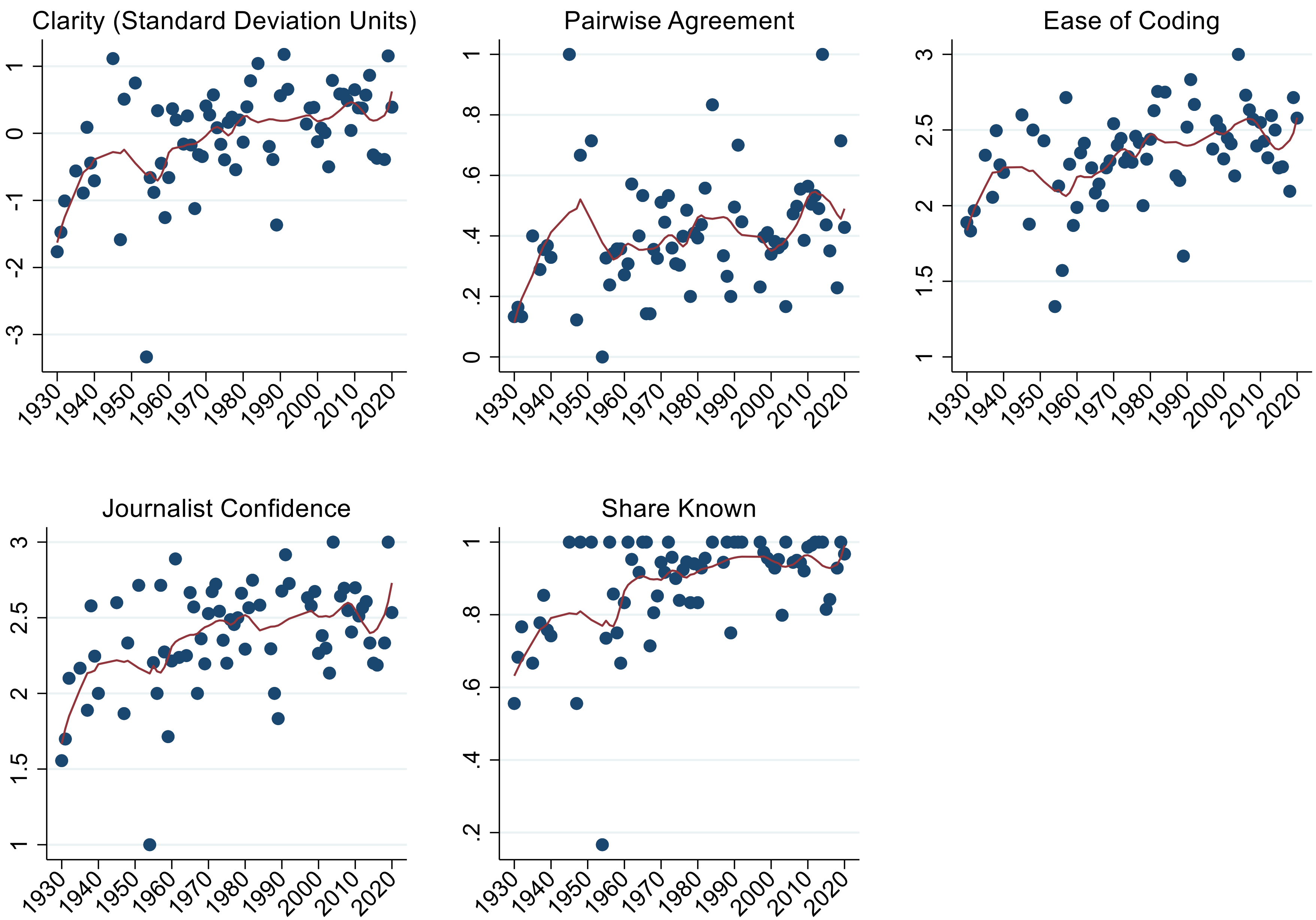
Figure A10: Volatility is Lower Around High-Clarity Jumps, U.S. Data from 1900 to 2023



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

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."

Table A1: Countries, Newspapers, and Jump Thresholds

Country	Years	Sources	Jump Threshold	Jump Frequency
United States	1990-2023	Wall Street Journal, Chicago Tribune, Financial Times, Los Angeles Times, New York Times, Washington Post	2.50%	3.51%
United Kingdom	1930-2020	Financial Times, Guardian, Times of London, Telegraph	2.50%	2.86%
Australia	1986-2020	Australian Financial Times, Sydney Morning Herald	2.50%	1.94%
Brazil	1972-2020	Folha de S. Paulo	3.00%	16.57%
Canada	1980-2020	The Globe and Mail, Toronto Star	2.00%	4.26%
China (Hong Kong)	1980-2020	South China Morning Post	3.80%	3.33%
France	1997-2020	Les Echos	2.50%	6.10%
Germany	1987-2020	Handelsblat, FAZ	2.50%	5.19%
Greece	2001-2015	Kathimerini, To Vima	4.00%	4.54%
India	1979-2020	The Times of India, Business Standard	3.50%	3.87%
Indonesia	1994-2020	Jakarta Post, Bisnis Indonesia	3.25%	4.06%
Ireland	1987-2020	The Irish Times	2.50%	5.01%
Japan	1981-2013	Yomiuri and Asahi	3.00%	3.94%
New Zealand	1996-2011	New Zealand Herald	2.50%	1.10%
Singapore	1989-2020	Business Times and Straits Times	2.50%	3.59%
South Africa	1986-2020	Business Day	2.50%	4.26%
South Korea	1982-2020	Chosun Ilbo, JoongAng Ilbo	3.50%	3.74%
Spain	1987-2020	ABC Madrid	2.50%	6.91%
Turkey	1987-2020	Cumhuriyet	3.50%	12.29%

Notes: The jump threshold is the minimum absolute return required for a day to be considered a jump in each country. We allow for differences across countries to account for differences in unconditional volatility.

Table A2: Regression Models Fit to Daily Industry-Level Equity Returns from 1960 to 2016

	Banks		*Pooled Sample*	
	(1) All Days	(2) Jump Days	(3) All Days	(4) Jump Days
γ Coefficient	0.80***	0.74***	0.55***	0.51***
(St. Error)	(0.23)	(0.24)	(0.13)	(0.13)
Observations	13,469	339	109,760	4720
R-Squared	0.67	0.83	0.56	0.81

Notes: See the appendix for the regression specification and the interpretation of the γ coefficient. We use Fama-French industry-level returns data. A single-industry regression for Guns, yields results similar to the Pooled Sample, but the standard error is large and the coefficient estimate is insignificant. When we set *Tri*=-1 for the Aerospace industry for jumps attributed to Sovereign Military Conflict, the Aerospace regression yields a small, marginally significant coefficient of the wrong sign. That may reflect the ambiguous nature of Aerospace firms' responses to military conflict: (relatively) good news for defense-oriented aerospace firms may, at the same time, be bad for aerospace firms oriented toward civilian customers. If we set *Tri*=1 for Aerospace in jumps attributed to Sovereign Military Conflict, the anomalous Aerospace result disappears, and the Pooled Sample results get stronger. *** p<0.01, ** p<0.05, * p<0.1

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:

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

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 A6: Volatility Following Policy and Non-Policy Jumps, US, 22-day

		Next 22 Days				Next 5 Days	
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Policy	3.557***	0.24				
		(0.549)	(0.344)				
	Non-Policy	5.292***	1.460***				
		(0.722)	(0.466)				
Non-Policy	Commodities			6.863***	1.679*	9.063***	2.442
				(1.208)	(0.879)	(2.093)	(1.541)
	Corporate Earnings			3.645***	0.786	3.771***	-0.0888
				(0.762)	(0.514)	(1.104)	(0.782)
	Macro News			4.763***	1.298**	5.815***	1.321
				(0.770)	(0.507)	(0.964)	(0.870)
Policy	Monetary Policy			2.105***	-0.642	1.683***	-1.863***
				(0.599)	(0.523)	(0.592)	(0.573)
	Fiscal Policy			6.596***	1.622	7.331***	0.989
				(1.569)	(1.304)	(1.676)	(1.205)
	Sovereign Military			1.533***	-0.545	3.258***	0.292
				(0.392)	(0.373)	(0.861)	(0.799)
	Obs	33,518	33,496	33,518	33,496	33,496	33,496
	R-Squared	0.101	0.325	0.116	0.325	0.105	0.312
	Return Controls	NO	YES	NO	YES	NO	YES
	HAR Controls	NO	YES	NO	YES	NO	YES
	F-Test for joint equality of coefs.	0.00179	0.0111	5.89E-05	0.0168	2.26E-05	0.00516

Notes: Columns 1-4 represent regressions, where the left-hand-side is the average percentage squared return in the 22 days following the jump. In columns 5-6, the left-hand-side is the average percentage squared return in the 5 days following the jump. US data, 1900-2023. There are only dummy variables for the jump categories shown, as well as a residual category which includes all the non-enumerated categories. Fiscal policy includes government spending and taxes. Enumerated categories represent the categories with the highest number of jumps by policy/non-policy groups. Non-policy excludes unknown. Columns 1 to 4: Newey-West standard errors with 33 lags. Columns 5 and 6: Newey-West standard errors with 8 lags.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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)
osolute 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 A8: Jump Clarity and Geographic Origin

Dependent Variable: Simplified Clarity

	(1)	(2)	(3)	(4)
Foreign	0.632***	0.191	0.289***	0.287***
	(0.181)	(0.279)	(0.054)	(0.053)
Observations	1,162	345	5,508	5,853
R-squared	0.058	0.087	0.018	0.036
Country Sample	US	US	ROTW	All
Years Sample	1900-2023	1980-2020	1980-2020	1980-2020
Fixed Effects	None	None	Country	Country
Standard Error Clusters	Year	Year	Country/Year	Country/Year
Mean LHS	0.00	0.56	0.00	0.03
SD LHS	1.00	0.80	1.00	1.00

Note: Each column reports a separate regression of Simplified Clarity on Foreign, a constant and controls for jump size, jump direction, and market volatility over the prior day, week and month. To measure Simplified Clarity, we sum Ease of Coding and Journalist Confidence, each normalized to have mean zero and unit standard deviation over time within a country. We further re-normalize this sum to have mean zero and unit standard deviation by country. We drop jumps that all readers attribute to Unknown & No Explanation and those with no next-day article. For a given human reading, Foreign equals 1 if the geographic origin field contains the home country only, ½ if it contains the home country and another country (or region), and 0 otherwise. We then average over all reads for a given jump to obtain the jump-level value of Foreign. When computing standard errors, we cluster errors by year in columns 1 and 2 and by country and year in columns 3 and 4. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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.