

Policy News and Stock Market Volatility

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Abstract: We create a newspaper-based Equity Market Volatility (EMV) tracker that moves with the VIX and with the realized volatility of returns on the S&P 500. Parsing the underlying text, we find that 72 percent of EMV articles discuss the Macroeconomic Outlook, and 44 percent discuss Commodity Markets. Policy news is another major source of volatility: 35 percent of EMV articles refer to Fiscal Policy (mostly Tax Policy), 30 percent discuss Monetary Policy, 25 percent refer to one or more forms of Regulation, and 13 percent mention National Security matters. The contribution of particular policy areas fluctuates greatly over time. Trade Policy news, for example, went from a virtual nonfactor in equity market volatility to a leading source after Donald Trump's election and especially after the intensification of U.S-China trade tensions. The share of EMV articles with attention to government policy rises over time, reaching its peak in 2017-18. We validate our measurement approach in various ways. For example, tailoring our EMV tracker to news about petroleum markets yields a measure that rises and falls with the implied and realized volatility of oil prices.

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The history of thought in financial markets has shown a surprising lack of consensus about a very fundamental question: what ultimately causes all those fluctuations in the price of speculative assets like corporate stocks...? One might think that so basic a question would have long ago been confidently answered.

Robert Shiller, 2014

1. Introduction

Volatility in aggregate equity returns is resistant to convincing interpretation. Shiller's classic 1981 contribution shows that stock market ups and downs cannot be rationalized by realized future dividends discounted at a constant rate.¹ Partly motivated by Shiller's demonstration, one major line of research stresses time-varying expected returns in asset-pricing models with rational agents. Another prominent line, also partly motivated by Shiller, stresses non-rational beliefs, limits to arbitrage, and fads that move equity prices in ways not fully tethered to real investment opportunities.² See Cochrane (2017) and Barberis (2018) for recent reviews.

We develop new data and evidence that inform rational and behavioral interpretations of the volatility in equity returns. In a first step, we identify articles about stock market volatility in leading U.S. newspapers and use them to construct an Equity Market Volatility (EMV) tracker. Figure 1 displays the resulting measure, which runs from January 1985 to October 2018 and is scaled to match the mean value of the VIX from 1985 to 2015. Our EMV tracker moves closely with the VIX and the realized volatility of daily returns on the S&P 500, with correlations of about 0.8 (0.85) in monthly (quarterly) data. As we show below, a narrower EMV tracker tailored to news about petroleum markets correlates well with the implied and realized volatility of oil prices. Another EMV tracker, which we tailor to macroeconomic news, surges in the wake of episodes that involve unusually high uncertainty about the near-term macroeconomic outlook – e.g., the October 1987 stock market crash, the 9-11 terrorist attacks, the March 2003 invasion of Iraq, the Global Financial Crisis, and the U.S. debt-ceiling crisis in summer 2011. These results suggest that our EMV trackers capture important drivers of fluctuations in equity market volatility.

¹ See, also, LeRoy and Porter (1981), Campbell and Shiller (1987, 1988), West (1988), Schwert (1989), Cochrane (1992) and Barberis, Huang and Santos (2001), among many others. Cochrane (1991) stresses the equivalence of excess volatility to return predictability.

² On the difficulty of drawing confident inferences about the presence of such fads, see Summers (1986), Fama and French (1988) and Poterba and Summers (1988).

In a second step, we parse the text in the EMV articles to quantify journalist perceptions about the news items, developments, concerns, and anticipations that drive volatility in equity returns. We classify these proximate drivers into about thirty categories, many of which pertain to particular types of policy. This approach lets us assess the importance of each category to the average level of stock market volatility and its movements over time. An immediate result is the importance of news about the Macroeconomic Outlook, broadly defined, which receives attention in 72% of all articles that enter into our EMV tracker. Most EMV articles discuss multiple topics. Thus, we also find that 44 percent mention Commodity Market developments, 31 percent mention Interest Rates, and 8 percent mention Financial Crises.

The policy share of EMV articles rises over time, reaching peaks in the 2001-03 period (9/11 and Iraq Invasion), the 2011-12 period (U.S. debt-ceiling crisis and the “fiscal cliff”), and the period since Donald Trump’s election in November 2016. Parsing the role of policy more finely, we find that 35 percent of EMV articles refer to Fiscal Policy (mostly Tax Policy), 30 percent mention Monetary Policy, 25 percent mention Regulation, and 13 percent mention National Security matters. We also construct EMV trackers tailored to these policy categories and find that each one fluctuates markedly over time. For example, our National Security EMV tracker is low in most periods but highly elevated after the 9/11 terrorist attacks and around Gulf Wars I and II. Trade Policy matters went from a virtual nonfactor for equity market volatility in the twenty years before Donald Trump’s election to a leading source afterwards, especially since the intensification of U.S-China trade tensions from March 2018.

How should we interpret these findings? According to the efficient markets view, equity price movements reflect genuine news that alters rationally grounded forecasts of future earnings and discount factors. Under this view, it’s natural to interpret news reports as a catalog of the rational forces that drive the volatility of equity returns. Shiller (2014, 1496-97) articulates a rather different view: “The market fluctuates as the sweep of history produces different mindsets at different points of time, different zeitgeists.... [A]ggregate stock market price changes reflect inconstant perceptions, changes that Keynes referred to with the term ‘animal spirits.’” Under this view, we expect newspaper articles to (imperfectly) mirror these mindsets and their shifts over

time.³ Under either view, we see our methods and measures as helpful in efforts to address the “basic question” posed in the epigraph.

Our EMV trackers have several noteworthy attributes: First, their construction is straightforward, transparent, easy to refine, and simple to replicate. Second, the frequency and volume of newspaper text affords much scope for granular characterizations of the forces that underlie equity market volatility and its movements over time. We develop several tailored EMV trackers that exploit this granular richness. Third, our text-based approach is useful for assessing the role of wars, policy risks, and other hard-to-quantify sources of stock market volatility. Fourth, our measurement methods are highly scalable across countries and over time. Although we focus on the volatility of aggregate U.S. equity markets from 1985 onwards, our methods extend readily to any country or time period with digital newspaper archives and data on aggregate equity returns. Finally, we update our EMV trackers monthly in real time.⁴ These real-time updates facilitate efforts to assess the out-of-sample performance of our measures.

There is a vast literature on equity returns and stock market volatility. Fama (1981), Chen, Roll and Ross (1986), and Fama and French (1989) are influential early studies that relate equity returns to macroeconomic forces. More recent contributions include Boyd et al. (2005) on stock market reactions to unemployment news, Killian and Park (2009) on the role of oil price shocks, and Bekaert et al. (2013) on the relationship between monetary policy and stock market volatility.

In one of the first studies to use newspaper text, Niederhoffer (1971) considers “world events” from 1950 to 1966 – as indicated by large headlines in the *New York Times* – and relates them to U.S. stock market movements. Cutler, Poterba and Summers (1989) relate returns on U.S. equities to macroeconomic data and news accounts of “political and world events.” They conclude that it’s hard to explain more than half the variation in aggregate stock prices by information in these sources about discount rates and future cash flows. Baker, Bloom, Davis, and Sammon (2019) consider thousands of daily stock market moves greater than $|2.5\%|$ in fourteen national markets. Based on systematic human readings of next-day newspaper accounts, they find that journalists attribute 37% of large daily moves in the United States to news about government policy. Evidence that policy developments move stock markets resonates with the theoretical work of Pastor and

³ Shiller (2014, page 1497) also writes “News media tend to slant their stories toward ideas of current interest, rather than useful facts that readers no longer find interesting.” Our results help in forming a judgement regarding that claim as well.

⁴ Our EMV trackers are available at policyuncertainty.com/EMV_monthly.html.

Veronesi (2012, 2013), who model the role of government policy as a source of economic uncertainty and the resulting implications for risk premia and equity prices.

Another line of research explores the usefulness of stock market volatility, as measured by the VIX, for predicting and assessing other important financial and economic variables. Nagel (2012) shows the VIX to be highly predictive of the return on liquidity provision. Dreschler and Yaron (2011) show that the equity variance premium – the squared VIX minus the expected realized variance – has predictive power for stock returns. Forbes and Warnock (2012) and Rey (2018) document global patterns in capital flows, asset prices and credit growth that are closely tied to the VIX. Our EMV trackers offer a new means to identify which developments underlie the relationships of stock market volatility to other outcomes of interest uncovered in earlier works.

Finally, we contribute to the rapidly growing body of research in economics and finance that applies text-based methods. Gentzkow, Kelly, and Taddy (2018) offer an excellent survey of research in this area. Here, we mention a few papers that are closest to ours. Baker, Bloom and Davis (2016) construct newspaper-based indices of economic policy uncertainty. They find that stock price volatility reacts more strongly to their policy uncertainty indices in firms with greater exposure to policy risks. Hassan et al. (2019) apply tools from computational linguistics to conference calls about earnings announcements to construct time-varying, firm-level measures of political risks. Their text-based measures also have explanatory power for firm-level variation in stock price volatility. Davis and Seminario (2019) quantify firm-level policy risk exposures using the text in 10-K filings. Their measures account for much of the huge dispersion in firm-level stock returns in the wake of Donald Trump’s surprise victory in the 2016 presidential election. Kelly, Manela, and Moreira (2018) develop an econometric model of text usage, estimate the model on multiple text sources, and use the estimates to backcast, nowcast and forecast financial variables. Manela and Moreira (2017) apply machine-learning methods to front-page articles in the *Wall Street Journal* to develop an “NVIX” measure of stock market uncertainty and the perceived risk of rare disasters. They conclude that policy risks and especially war-related concerns are a major source of variation in equity risk premia, broadly in line with the literature on rare disasters and asset prices.⁵

⁵ See Rietz (1988), Barro (2006), Gourio (2008), Gabaix (2012) and Wachter (2013), among others.

2. Methodology

2.1 Constructing an Equity Market Volatility Tracker

In constructing our Equity Market Volatility (EMV) tracker, we follow Baker, Bloom and Davis (BBD) in using scaled frequency counts of newspaper articles that contain selected terms. We differ in our approach to term selection. They rely on human readings of 12,000 randomly sampled articles to populate a list of candidate terms. They then select the permutation of candidate terms that minimizes the sum of false positives and false negatives in computer-automated classifications compared to human classifications.⁶ Their approach makes sense in developing a measure of economic policy uncertainty, for which there is no obvious observable counterpart. We exploit the observability of stock market volatility to take a much less labor-intensive approach.

We first specify terms in three sets, as follows:

E: {economic, economy, financial}

M': {"stock market", stock OR stocks, "equity market", equity OR equities, S&P OR "S & P", "Standard and Poors" OR "Standard and Poor's" OR "Standard and Poor" OR "Standard & Poors" OR "Standard & Poor's"}

V': {volatility OR volatile, "realized volatility", uncertain OR uncertainty, risk OR risky, variance, VIX}

Second, we randomly select a 30% sample of articles that contain at least one element in each of **E**, **M'** and **V'** from 1990 to 2015.⁷ Third, using the sampled articles, we construct a candidate EMV tracker for each permutation of elements in **M'** and **V'**.⁸ Specifically, we count articles that contain the candidate permutation, scale that count by the number of all articles in the same paper and month, standardize the scaled frequency counts to unit standard deviation for each paper, and then average the resulting standardized, scaled counts over papers by month.⁹ Finally, we select the permutation that achieves the highest R-squared value in an OLS regression of the 30-day VIX on the candidate EMV tracker using monthly data from 1990 to 2015.

⁶ BBD use this procedure to select the "Policy" terms for their newspaper-based Economic Policy Uncertainty Index. Their approach to selecting terms in "Economy" and "Uncertainty" is similar in spirit but much less formal.

⁷ Here, we use four newspapers for which we could download many articles that meet our criteria: the Miami Herald, Dallas Morning News, San Francisco Chronicle, and Houston Chronicle.

⁸ We consider all permutations in $P(\mathbf{M}') \times P(\mathbf{V}')$, where $P(\bullet)$ denotes the power set and \times is the Cartesian product. "Equity market" never appears in our sample of articles, so we drop it. That leaves five elements in **M'** and six in **V'**, which yields $2^5 \times 2^6 = 2048$ permutations.

⁹ These mechanics follow Baker, Bloom and Davis (2016) exactly.

Log, level, and level specifications with quadratic and cubic terms yield the same best-fit permutation, given by

E: {economic, economy, financial}

M: {"stock market", equity, equities, "Standard and Poors" (and variants)}

V: {volatility, volatile, uncertain, uncertainty, risk, risky}

In the analyses below, our EMV tracker is based on this best-fit term set.

In assessing our term sets and our selection procedure, a few additional remarks will be helpful. We start with parsimonious **E**, **M'** and **V'** sets to reduce the danger of overfitting. While each regression in our selection procedure has few explanatory variables (just one, except when we add quadratic and cubic terms), we consider many such regressions. We eschew terms like "Lehman Brothers," "Bernanke" and "Iraq war" that might improve in-sample performance but perform poorly out of sample. And we prefer terms that extend easily to other countries and settings. Terms like "economy," "stock market," "volatility" and "uncertainty" translate readily, while terms like "Standard and Poors" have obvious counterparts for other national stock markets. In this respect, we regard it as fortuitous that "VIX" did not make the cut for our best-fit permutation, because there is no VIX counterpart for many national stock markets.

Armed with our best-fit term set, we obtain monthly counts of articles that contain at least one term in each of **E**, **M** and **V** for eleven major U.S. newspapers: the Boston Globe, Chicago Tribune, Dallas Morning News, Houston Chronicle, Los Angeles Times, Miami Herald, New York Times, San Francisco Chronicle, USA Today, Wall Street Journal, and Washington Post. At this stage, we use counts from the full set of articles published in each newspaper, not a sample, and we again scale by the count of all articles in the same paper and month.¹⁰ We then standardize the scaled counts and average over newspapers by month. In a final step, we multiplicatively rescale our best-fit EMV tracker to match the mean value of the VIX from 1985 to 2015.

Figure 1 displays our EMV tracker from January 1985 to October 2018.¹¹ The series exhibits pronounced upward spikes in reaction to the 1987 stock market crash, the 1998 Russian financial

¹⁰ The reader might wonder why we don't use all eleven papers in the term set selection procedure. The answer is purely one of feasibility. We cannot obtain a large sample of machine-readable articles for most newspapers. Nor can we put millions of queries to digital newspaper archives to cover all the permutations of **M'** and **V'**. Given the **E**, **M** and **V** sets, however, we need only two article counts per paper per month – the EMV count and the "all" count.

¹¹Data for the CBOE 30-day VIX starts in 1990. After selecting our best-fit term set using data from 1990 to 2015, we obtained the VIX data developed in Berger et al. (2019) back to 1983. Thus, our EMV tracker data before 1990 and after 2015 are "out of sample" in the sense that they are outside the period used in our term selection procedure.

crisis, the Enron and WorldCom accounting scandals and bankruptcies in 2001-2002, the full-force eruption of the financial crisis in September 2008, and the U.S. debt-ceiling crisis in the summer of 2011. Several other episodes triggered smaller spikes. We validate our EMV tracker, assess its performance in various ways, and consider robustness checks in Section 3 below. Before doing so, we explain how to construct our category-specific trackers.

2.2 Parsing the Text and Constructing Category-Specific Trackers

We parse the text in our best-fit EMV articles to quantify journalist perceptions about the particular forces that drive volatility in equity returns. As a first step, we classify these forces into 10 general economic categories and about 20 policy-related categories. These classifications provide a basis for assessing the importance of each category for the average level of stock market volatility and its movements over time.

Our classification approach is conceptually simple: If certain category-relevant terms appear in an EMV article, we infer that the article discusses one or more topics covered by the category in question. For example, consider our term sets for **Interest Rates** (one of our general categories) and **Monetary Policy** (one of our policy categories):

Interest Rates: {interest rates, yield curve, fed funds rate, overnight rate, repo rate, T-bill rate, bond rate, bond yield}

Monetary Policy: {monetary policy, money supply, open market operations, fed funds rate, discount window, quantitative easing, forward guidance, interest on reserves, taper tantrum, Fed chair, Greenspan, Bernanke, Volker, Yellen, Draghi, Kuroda, Jerome Powell, lender of last resort, central bank, federal reserve, the fed, European Central Bank, ecb, Bank of England, bank of japan, people's bank of china, pboc, pbc, central bank of china, Bank of Italy, Bundesbank}

If an EMV article contains one or more terms in **Interest Rates**, we infer that the article includes a discussion of interest rates; likewise, if it contains one or more terms in **Monetary Policy**, we infer that it discusses monetary policy. As these examples suggest, many EMV articles contain terms in more than one category. That is by design. We do not draw overly sharp boundaries between overlapping categories, nor do we aim to draw distinctions that are too fine for our text sources and methods. Appendix B sets forth a complete listing of our category-specific term sets.

Next, we calculate the share of EMV articles in each category and multiply by the EMV tracker value to obtain category-specific trackers. For example, to measure the importance of monetary policy considerations in equity market volatility during month t , we calculate

$$\left(\frac{\# \{E \cap M \cap V \cap \text{Monetary Policy}\}_t}{\# \{E \cap M \cap V\}_t} \right) EMV_t,$$

where $\#$ denotes the count of newspaper articles in the indicated set, and EMV_t is the value of our overall EMV tracker in month t . We use this same approach for all categories.

As before, a few additional remarks will be helpful in assessing our method. First, the overfitting concern that led us to start with parsimonious \mathbf{E} , \mathbf{M}' and \mathbf{V}' sets in developing our overall EMV tracker is no longer germane, because we have already identified our best-fit EMV articles. At this point, our goal is to capture and classify the full set of topics and concerns that animate discussions of stock market volatility in the EMV articles. Thus, several of our category-specific sets contain many terms. **Monetary Policy**, for example, has more than 25 terms. Other categories with lengthy term sets include **Macroeconomic News & Outlook**, **Commodity Markets**, **Taxes**, and **Financial Regulation**.

Second, while we deliberately avoid particularistic terms like “Bernanke” and “Iraq war” in constructing our overall EMV tracker, we embrace them in devising our category-specific term sets. The difference in approach reflects a difference in objectives. In developing our overall EMV tracker, we seek a measure with good prospects for fitting well out of sample and ready portability to other national stock markets and eras. In contrast, we design the category-specific term sets to characterize and quantify the specific forces that underlie stock market volatility and its variability over time and space. We recognize that our category-specific sets require considerable modification when applied to other countries and time periods. That is inherent in an effort to characterize forces that are specific to time and place. Still, our roughly 30 categories are portable over time and space, even when many of the category-specific terms are not.

Third, our term sets for the policy-related categories extend Baker, Bloom and Davis (2016) and Davis (2017). They populate their category-specific term sets by consulting textbooks, newspapers, “risk factor” discussions in 10-K filings, and other sources – including their own knowledge of economic matters and input from other economists in seminars and personal communications. We extend the policy-related term sets of BBD and Davis and build term sets for the general economic categories using the same basic approach. Thus, our classification approach

is expert-driven and judgmental, in contrast to the algorithmic use of external libraries to classify n -grams as in Hassan et al. (2019), who borrow methods from computational linguistics.

Table 1 considers all EMV articles from 1985 to 2017 and reports the percent that contain terms in each category.¹² The top row says that news and other remarks about the Macroeconomic Outlook feature very prominently, appearing in 72% of all EMV articles. News about Commodity Markets appear in 44% of EMV articles, while news about Interest Rates figures in 31%. Panel B in Table 1 considers our policy-related categories, including aggregated categories for Fiscal Policy and Regulation. Tax Policy and Monetary Policy each receive attention in 30% of EMV articles, the aggregated Regulation category features in 25%, and National Security matters figure in 13%. Most other categories play a small role over the 1985-2017 period as a whole, although they can become prominent in certain episodes, as we show below.

3. Validation and Robustness Checks

3.1 EMV Tracking Performance

Table 2 provides information about how well our EMV measure tracks monthly movements in stock market volatility from 1985 to 2018. As reported in column (1), regressing the VIX on contemporaneous EMV values yields a highly statistically significant slope coefficient of 0.76 and an R-squared value of 0.61. The first two lags of EMV are also statistically significant, and their inclusion raises the R-squared to 0.70. Adding lagged VIX pushes the R-squared value well above 0.8 and knocks out the statistical power of the lagged EMV terms, but the contemporaneous EMV term remains highly significant. Log-log specifications and regressions of realized stock market volatility on EMV yield similar results.

Figure 2 plots the VIX and the fitted values for the column (1) specification. For the most part, fitted values – and the underlying EMV values – move closely with the VIX. There are some exceptions: (i) fitted VIX jumps less than actual VIX in reaction to the October 1987 stock market crash, (ii) fitted VIX largely misses the VIX reaction to the Iraqi invasion of Kuwait in August 1990, (iii) fitted VIX persistently exceeds the VIX from 1993 to 1996 and 2005 to early 2007, and (iv) fitted VIX reverts to the mean more quickly than actual VIX after major upward spikes, a pattern that is most evident for the cataclysmic events of September-November 2008.

¹² The column entries sum to more than 100 percent for two reasons: First, because certain terms such as “Fed funds rate” appear in the term set for more than one category. Second, because many EMV articles refer to multiple sources of equity market volatility.

We could address (i) and (ii) by incorporating episode-specific terms like “Black Monday” and “Kuwait invasion” into our EMV term sets. We refrain from that approach for reasons discussed in Section 2.1. Fit errors of type (iv) reflect how press coverage evolves after surprise events that jolt financial markets. In the immediate wake of events like 9-11 and the 2011 U.S. debt-ceiling crisis, an outpouring of newspaper articles discusses the event and its bearing on stock market volatility. Elevated volatility levels persist, but press coverage abates as the event loses its newness. As a result, our EMV tracker drops relative to the VIX in the near-term aftermath of such events. A closer examination of regression residuals in Appendix Figure C.1 reinforces this interpretation. Figure C.2 shows that adding lagged VIX to the regression specification greatly dampens fit errors of type (iv), except for the stock market crash of 1987. While this temporal pattern in the residuals is an interesting commentary on press coverage, it does not undercut the usefulness of EMV for our purposes. In any event, adding lagged VIX to the regression specification largely resolves this type of tracking error as well as errors of type (iii).

3.2 Comparison to NVIX

Manela and Moreira (2017) construct a monthly news-based implied volatility (NVIX) measure using abstracts and headlines of front-page articles in the *Wall Street Journal*. From this text source, they create large “feature sets” of n -grams that serve as explanatory variables in support vector regressions fit to the VIX. While their method and text source differ from ours, the spirit of their statistical undertaking is similar. As another check on EMV, we now assess how it fares – with respect to similarity to the VIX – in comparison to NVIX. We use monthly data from January 1985 to March 2016 for this purpose, the longest overlap period for the three measures.

Table 3 reports summary statistics. EMV correlates with the VIX at 0.78, which compares to 0.70 for NVIX. The mean absolute monthly difference between EMV and VIX is 3.7 points, as compared to 4 points for NVIX. The EMV standard deviation, skewness, and kurtosis are much closer to the corresponding VIX statistics. Turning to Figure 3, we see that NVIX underperforms EMV in tracking the VIX during the second half of the 1980s and from 2012 to 2015. NVIX performs better than EMV in 1990 around the time of the Iraqi invasion of Kuwait.

In summary, each measure has weaknesses and strengths, but EMV outperforms NVIX in tracking the VIX and matching its moments. A big reason for EMV’s superior performance is its reliance on a much larger text corpus – the full text of eleven major newspapers, as compared to abstracts and headlines of front-page articles in a single paper. In fact, when we rerun specification

(1) in Table 2 using an EMV measure based on a single paper, the R-squared value drops drastically – by 17 to 38 percentage points. See Appendix Table C.2.¹³

3.3 Robustness to Alternative Newspaper Weightings

We also assess the assumption, implicit in our method, that each newspaper is equally useful (on the margin) in tracking equity market volatility. To do so, we double the weight on each newspaper, one at a time, in constructing EMV. Then we rerun specification (1) in Table 2 using the EMV tracker based on the modified newspaper-level weights. Table C.2 reports the results. Doubling the weight on the *Wall Street Journal* or the *Miami Herald* yields an incremental R-squared gain of .002 to .004. Doubling the weight on the *San Francisco Chronicle* leaves the R-squared unchanged, and doubling the weight on any other paper lowers the R-squared, with a maximal drop of 0.011. We also drop each newspaper, one at a time, and repeat the exercise. In two cases, dropping the paper yields a modest fit improvement, in one case it has no effect, and in the other eight cases fit deteriorates modestly. The largest absolute change in the R-squared value from dropping newspapers is only 0.013.

We draw three conclusions from these results. First, tracking performance improves greatly by drawing on multiple newspapers. Second, the performance of our preferred EMV measure is robust to alternative newspaper weightings on the margin (i.e., given eleven papers in our baseline). Third, while using multiple newspapers yields huge performance gains, the gains are subject to strong diminishing returns. Eleven papers appear sufficient to exhaust the gains. Of course, we cannot preclude the possibility that an untried newspaper would materially improve EMV tracking performance. However, even the financially-oriented *Wall Street Journal* matters little on the margin, which casts doubt on the notion that an untried paper would add a lot.

3.4 A Petroleum Markets EMV Tracker

We now subject our method to a different type of assessment, one that is especially pertinent for our category-specific measures. Specifically, we construct a Petroleum Markets EMV tracker and compare it to observed measures of oil price volatility. To that end, define a **Petroleum Markets** term set, {oil, petroleum, Alaska pipeline, Keystone pipeline}, and compute

¹³ In Appendix Table C.1, we also show that EMV and NVIX each have independent explanatory power in VIX regressions, regardless of whether we control for lagged VIX. This pattern suggests that applying machine-learning methods to the full text of our eleven newspapers would materially improve on our EMV tracker. Of course, implementing such an approach requires direct access to the full text of each paper.

$$\left(\frac{\#\{E \cap M \cap V \cap \text{Petroleum Markets}\}_t}{\#\{E \cap M \cap V\}_t} \right) EMV_t.$$

This Petroleum Markets EMV tracker correlates at 0.59 with the CBOE Crude Oil Volatility Index (0.68 in quarterly data) from 2007 to 2018 and at 0.52 with the CBOE Crude Oil Realized Volatility (0.57 in quarterly data) from 1986 to 2018. Inspecting Figure 4 confirms that our measure mirrors many of the movements in oil price volatility. It also misses badly in certain episodes, e.g., after the stock market crash of 1987 and during the Global Financial Crisis. These episodes involve much larger jumps in stock price volatility than oil price volatility. Hence, it's no surprise that our measure, with its focus on equity markets, remains highly sensitive to these events even when we narrow its scope to petroleum markets. Nor is this sensitivity a problem for our purposes, given that we aim to characterize the sources of *equity* market volatility.

In summary, Figure 4 gives assurance that our category-specific EMV trackers capture variation in the role of the corresponding topics and concerns as drivers of equity market volatility. We interpret our category-specific EMV trackers accordingly.

4. What Drives Fluctuations in Stock Market Volatility?

4.1 News About the Economic Outlook

Figure 5 displays our EMV tracker for **Macroeconomic News and Outlook**, which contains about 80 terms and reflects an expansive conception of the category. Since topics covered by this category appear in 72 percent of EMV articles (Table 1), Macro EMV moves similarly to overall EMV and to the VIX. For example, the Macro EMV tracker jumps in reaction to the October 1987 stock market crash, the Russian Financial Crisis, the Global Financial Crisis, and the debt-ceiling crisis in summer 2011 – episodes that involved major upsurges in uncertainty about the macroeconomic outlook. In contrast, the Enron and WorldCom scandals – which arguably injected little uncertainty about the macro outlook – generated a muted response in Macro EMV relative to overall EMV (Figure 1) and relative to the VIX (Figure 2).

Our method is easily adapted to more tightly focused EMV trackers. As an illustration, Figure 6 plots a Financial Crisis EMV tracker based on the following term set: {financial crisis, financial crises, Northern Rock failure, Lehman failure, Lehman Brothers failure, AIG Takeover, euro crisis, Eurozone crisis, Greek crisis}. Two events stand out in the evolution of this EMV tracker: the Global Financial Crisis, and the U.S. debt-ceiling crisis of 2011. The Mexican Peso Crisis of 1994, the Asian and Russian Financial Crises of 1997-98, and concerns related to Greece and

China in 2015 also leave clear marks on our Financial Crisis EMV tracker. Interestingly, the tracker’s baseline level is consistently higher after the Global Financial Crisis, which suggests that the GFC prompted a persistent shift in perceptions about the relevance of financial crises to U.S. stock market volatility.

4.2 The Growing Role of Policy Matters

Figure 7 reveals an upward drift in the fraction of EMV articles that devote attention to policy matters, with peaks in the 2001-03 period (9/11 and Iraq Invasion), the 2011-12 period (U.S. debt-ceiling crisis and the “fiscal cliff”), and the period since Donald Trump’s presidential election in November 2016. To construct Figure 7, we sum EMV article counts over the policy-related categories in Table 1 and divide by the EMV article count summed over all categories – both general economic and policy-related categories.¹⁴ We take this approach, because limits on the number of terms per search query prevent us from directly computing the share of EMV articles that contain one or more of our policy-related terms. As a robustness check, we performed the direct calculation using the much smaller set of “Policy” terms in the Economic Policy Uncertainty Index.¹⁵ This alternative calculation, reported in Appendix Figure C.3, also shows an upward drift in the policy fraction of EMV articles, broadly in with Figure 7.

This upward drift suggests a growing role for policy concerns in U.S. stock market volatility. It resonates with other evidence of an expanding government role in the economy and an upward trend in policy-related economic uncertainty, as discussed in Baker et al. (2014) and Davis (2017): secular growth in government expenditures as a share of GDP, the increasing scale and complexity of the regulatory system, the increasing complexity of the federal tax code, the growing share of business “risk factors” that U.S. firms attribute to government policy in their 10-K filings, a secular rise in the newspaper-based Economic Policy Uncertainty Index of Baker, Bloom and Davis (2016), an upward drift in the frequency with which the Federal Reserve System’s Beige Books refer to policy uncertainty, and a secular rise in U.S. political polarization that has drawn enormous attention from political scientists. On this last point, see, e.g., McCarty, Poole and Rosenthal (2016). Since these long-term developments show little sign of reversal, policy concerns are likely to remain a major source of stock market volatility for many years.

¹⁴ For Fiscal Policy and Regulation, we use article counts for the more disaggregated categories.

¹⁵ Their Policy term set is {regulation, regulations, regulatory, deficit, deficits, legislation, legislative, legislature, white house, federal reserve, the fed, congressional, congress, war, tariff.}

As suggested by the annotations in Figure 7, the mix of policy-related factors in stock market volatility varies over time. We can use our category-specific term sets to develop this point in a systematic, quantitative manner. As an illustration, Figure 8 displays the percent of EMV articles by month that contain one or more terms in **Trade Policy**. The figure shows a dramatic upsurge in trade policy concerns as a source of stock market volatility after Donald Trump's election. Days after his inauguration, President Trump pulled the United States out of the Trans-Pacific Partnership, which had yet to be ratified. He threatened to jettison the North American Free Trade Agreement, triggering contentious trade negotiations with Canada and Mexico. The Trump administration also imposed tariff hikes on steel, aluminum and other goods and has threatened to impose many more. Since March 2018, the United States has ratcheted up tariffs and tariff threats with China, and the China has responded in kind. These are among the developments that took trade policy concerns from a virtual nonfactor in U.S. stock market volatility to a leading source.¹⁶

4.3 Policy-Related EMV Compared to Economic Policy Uncertainty

We now construct a Policy-Related EMV tracker and compare it to the Economic Policy Uncertainty Index of Baker, Bloom and Davis (2016). While both measures rely on scaled frequency counts of newspaper articles, they are conceptually distinct. The EPU Index aims to quantify policy-related uncertainty for the economy as a whole. The Policy-Related EMV tracker aims to quantify the full range of policy-related volatility sources for the stock market in particular. To obtain our Policy-Related EMV tracker, we multiply the overall EMV tracker in Figure 1 by the policy-related fraction in Figure 7. We then multiplicatively rescale to match the mean EPU value from 1985 to 2009, so that we can readily compare the two series.

Figure 8 displays the comparison. The two measures react to many of the same developments but also show systematic differences. Stock market crashes and financial crises leave larger marks on Policy-Related EMV. National security developments, national elections, and fiscal policy conflicts are more visible in the EPU Index.

Panel B in Table 1 makes a closely related point. Financial Regulation receives attention in 25% of EMV articles as compared to 6% of EPU articles. In contrast, National Security, Healthcare Policy, and Entitlement and Welfare Programs are among the policy-related categories that loom larger for Economic Policy Uncertainty than Equity Market Volatility. On the whole, policy-

¹⁶ For a fuller account of trade policy developments since the November 2016 election, see the Trade War Timeline in Brown and Kolb (2019).

related discussions appear more frequently in EPU than in EMV articles. That’s sensible and reassuring, because we use “policy” terms in identifying EPU articles.

4.4 A Suite of Policy-Related EMV Trackers

We now implement the method in Section 2.2 to construct a suite of policy-related EMV trackers. Figures 10, 11 and 12 display EMV trackers for monetary and fiscal policy categories. Certain events loom large in all three trackers: the stock market crash of October 1987 and the debt-ceiling crisis of 2011. Certain events are particularly prominent in the Monetary Policy EMV tracker: the start of QE1 and QE2, the Taper Tantrum, and the July 2015 Greek Referendum that shook the Eurozone. Other events are more prominent in the Tax Policy EMV tracker: the Bush Tax Cuts of 2001 and 2003, the Fiscal Cliff episode in late 2012 and early 2013, and the Tax Cut and Jobs Act enacted in November 2017. Yet other events are prominent in the EMV tracker for Government Spending, Deficits and Debt: the Government Shutdowns of 1995-96 and 2013 and the Fiscal Cliff.

The EMV tracker for Financial Regulation in Figure 13 shows large upward spikes around the enactment of the Sarbanes-Oxley Act of 2002, during the Global Financial Crisis, and around the time of the Dodd-Frank Act of 2010. The EMV tracker for Elections and Political Governance in Figure 14 fluctuates at low levels except for short time windows around the U.S. presidential elections of 2000, 2016 and, to a lesser extent, 1992. The National Security EMV tracker in Figure 15 exhibits large upward spikes around Gulf War I, the 9-11 attacks, and the early stages of Gulf War II. EMV trackers for Healthcare Policy and Trade Policy (Figures C.6 and C.7) also show distinctive fluctuations. All of the underlying data for these figures, and more, are available at http://www.policyuncertainty.com/EMV_monthly.html, with regular monthly updates.

To summarize, these figures show highly distinctive temporal movements in the category-specific EMV trackers. Certain events, most notably the market crash of 1987, leave a strong mark in most or all of the category-specific trackers. Many other events, however, leave a strong mark in only one or a few of the category-specific trackers. The distinctiveness of the temporal patterns in the category-specific trackers is potentially quite useful in downstream econometric work that seeks to explain firm-level outcomes.

5. Summary and Directions for Research

We develop a simple, transparent, scalable method for constructing newspaper-based Equity Market Volatility (EMV) trackers. Implementing the method using eleven major U.S. newspapers, our EMV tracker moves closely with the VIX and with realized volatility on the S&P 500.

We also parse the text in the EMV articles to quantify journalist perceptions about the forces that underlie stock market volatility and its movements over time. We classify these forces into about thirty categories – including Macroeconomic News, Monetary Policy, Tax Policy and Financial Regulation – and construct a tailored EMV tracker for each category. This exercise reveals an upward drift over time in the role of policy as a source of stock market volatility, as measured by the share of EMV articles that discuss policy-related matters. It also reveals Monetary Policy and Tax Policy to be the most important policy-related sources of stock market volatility, followed by our aggregated Regulation category. The contribution of specific policy categories to stock market volatility fluctuates markedly over time.

There are several natural directions for future research. First, we are currently using our category-specific EMV trackers to explain and interpret the distribution of firm-level stock price volatilities and its movements over time. Second, our methods extend readily to any country or time period with digital newspaper archives and data on aggregate equity returns. By developing EMV trackers for multiple countries, one can explore the specific global and national forces that underlie stock market volatilities around the world. Third, our basic approach could be usefully applied to construct and parse newspaper-based trackers for other concepts. It would be straightforward, for example, to adapt our methods to construct newspaper-based trackers of consumer confidence, business sentiment and the like, and to delve into the specific forces that drive their movements.

References

- Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold, 2002. "Range-Based Estimation of Stochastic Volatility Models," *Journal of Finance*, 57, 1047-1092.
- Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, 2003. "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange," *American Economic Review*, 93, 38-62.
- Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, 2007. "Real-Time price discovery in global stock, bond, and foreign exchange markets," *Journal of International Economics*, 73, 251-277.
- Bachmann, Rüdiger, Steffen Elstner, and Eric R. Sims, 2013. "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5, 2, 217-49.
- Baker, Scott, Nicholas Bloom, Brandice Canes-Wrone, Steven J. Davis and Jonathan Rodden, 2014. "Why Has Policy Uncertainty Risen Since 1960," *American Economic Review, Papers & Proceedings*, 104, no. 5 (May), 56-60.
- Baker, Scott, Nicholas Bloom and Steven J. Davis, 2016. "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131, no. 4 (November), 1593-1636.
- Baker, Scott, Nicholas Bloom, Steve J. Davis and Marco Sammon, 2019. "What triggers stock market jumps?" work in progress presented at the January 2019 ASSA meetings.
- Barro, Robert J., 2006. "Rare Disasters and Asset Markets in the Twentieth Century," *American Economic Review*, 121, no. 3, 823-856.
- Barberis, Nicholas, 2018. "Psychology-Based Models of Asset Prices and Trading Volumes," forthcoming in D. Bernheim, S DellaVigna and D. Laibson, editors, *Handbook of Behavioral Economics*. North Holland, Amsterdam.
- Barberis, Nicholas, Ming Huang and Tano Santos, 2001. "Prospect Theory and Asset Prices," *Quarterly Journal of Finance*, 116, no. 1, 1-53.
- Bekaert, Geert, Marie Hoerova and Marco Lo Duca, 2013. "Risk, Uncertainty and Monetary Policy," *Journal of Monetary Economics*, 60, 771-778.
- Berger, David, Ian Dew-Becker, and Stefano Giglio, 2019. "Uncertainty shocks as second-moment news shocks," forthcoming in the *Review of Economic Studies*.
- Boyd, John H., Jian Hu and Ravi Jagannathan, 2005. "The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks," *Journal of Finance*, 60, no. 2 (April), 649-672.
- Brown, Chad P. and Melina Kolb, 2019. "Trump's Trade War Timeline: An Up-to-Date Guide," at <https://piie.com/blogs/trade-investment-policy-watch/trump-trade-war-china-date-guide>.
- Campbell, John Y. and Robert J. Shiller, 1987. "Cointegration and Tests of Present-Value Models," *Journal of Political Economy*, 95, 1062-1088.
- Campbell, John Y. and Robert J. Shiller, 1988. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, 1, no. 3 (July), 195-228.
- Chen, Nai-Fu, Richard Roll and Stephen A. Ross, 1986. "Economic Forces and the Stock Market," *Journal of Business*, 59, no. 3 (July), 383-403.
- Christensen, B.J. and N.R. Prabhala, 1998. "The relation between implied and realized volatility," *Journal of Financial Economics*, 50, 2, 125-150.

- Cochrane, John H., 1991. "Volatility Tests and Efficient Markets: A Review Essay," *Journal of Monetary Economics*, 27, 463-485.
- Cochrane, John H., 1992. "Explaining the Variance of Price-Dividend Ratios," *Review of Financial Studies*, 5, no. 2 (April), 243-280.
- Cochrane, John H., 2017. "Macro-Finance," *Review of Finance*, 21, no. 3 (May), 945-985.
- Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1989. "What moves stock prices?" *Journal of Portfolio Management*, 15, no. 3 (Spring), 4-12.
- Davis, Steven J., 2017. "Regulatory Complexity and Policy Uncertainty: Headwinds of Our Own Making," paper prepared for the Hoover Institution Conference on Restoring Prosperity: Contemporary and Historical Perspectives.
- Davis, Steven J. and Cristhian Seminario, 2019. "Diagnosing the Stock Market Reaction to Trump's Surprise Election Victory," University of Chicago, in progress.
- Drechsler, Itamar and Amir Yaron, 2011. "What's Vol Got to Do with It?" *The Review of Financial Studies*, 24, 1, 1-45.
- Fama, Eugene F., 1981. "Stock Returns, Real Activity, Inflation, and Money," *American Economic Review*, 71, no. 4 (September), 545-565.
- Fama, Eugene F. and Kenneth R. French, 1988. "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy*, 96, 246-273.
- Fama, Eugene F. and Kenneth R. French, 1989. "Business Conditions and Expected Returns on Stocks and Bonds," *Journal of Financial Economics*, 25, 23-49.
- Forbes, Kristin J. and Francis E. Warnock, 2012. "Capital Flow Waves: Surges, Stops, Flight and Retrenchment," *Journal of International Economics*, 88, no. 2, 235-251.
- Gabaix, Xavier, 2012. "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance," *Quarterly Journal of Economics*, 127, no. 2, 645-700.
- Gentzkow, Matthew, Bryan T. Kelly, and Matt Taddy, 2018. "Text as data," *Journal of Economic Literature* (Forthcoming).
- Gorodnichenko, Yuriy and Michael Weber, 2016, "Are Sticky Prices Costly? Evidence from the Stock Market," *Economic Review*, 106, 1, 165-199.
- Gourio, Francois, 2008. "Time Series Predictability in the Disaster Model," *Finance Research Letters*, 5, no. 4, 191-203.
- Hassan, Tarek A., Stephan Hollander, Laurence van Lent and Ahmed Tahoun, 2019. "Firm-Level Political Risk: Measurement and Effects," working paper.
- Jurado, Kyle, Sydney Ludvigson, and Serena Ng, 2015. "Measuring Uncertainty," *American Economic Review*, 105 (3), 1177-1216.
- Kelly, Bryan, Asaf Manela, and Alan Moreira, 2018. "Text Selection," working paper, October.
- Killian, Lutz and Cheolbeom Park, 2009. "The Impact of Oil Price Shocks on the U.S. Stock Market," *International Economic Review*, 50, no. 4 (November), 1267-1287.
- Londono, Juan M. and Beth Anne Wilson, 2018. "Understanding Global Volatility," *IFDP Notes*, January 2018.
- Manela, Asaf and Alan Moreira, 2017. "News implied volatility and disaster concerns," *Journal of Financial Economics*, 123, no.1, 137-162.
- McCarty, Nolan, Keith T. Poole and Howard Rosenthal, 2016. *Polarized America: The Dance of Ideology and Unequal Riches*, second edition. Cambridge, MA: MIT Press.
- Nagel, Stefan, 2012. "Evaporating Liquidity," *Review of Financial Studies*, 25, 7, 2005-2039.
- Niederhoffer, Victor, 1971. "The Analysis of World Events and Stock Prices," *Journal of Business*, 44 (April), 193-319.

- Pastor, Lubos and Pietro Veronesi, 2012. "Uncertainty about Government Policy and Stock Prices," *Journal of Finance*, 64, 4, 1219-1264.
- Pastor, Lubos and Pietro Veronesi, 2013. "Political Uncertainty and Risk Premia," *Journal of Financial Economics*, 110, 3, 520-545.
- Poterba, James and Lawrence Summers, 1988. "Mean Reversion in Stock Prices," *Journal of Financial Economics*, 22, 27-59.
- Rey, Helene, 2018. "Dilemma Not Trilemma: The Global Financial Cycle and Monetary Policy Independence," NBER Working Paper 21162, revised.
- Rietz, Thomas A., 1988. "The Equity Risk Premium: A Solution," *Journal of Monetary Economics*, 22, no. 1, 117-131.
- Schwert, G. William, 1989. "Why Does Stock Market Volatility Change Over Time?" *Journal of Finance*, 44, no. 5 (December), 1115-1153.
- Shiller, Robert J., 1981. "Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends?" *American Economic Review*, 71, no. 3 (June), 421-436.
- Shiller, Robert J., 1984. "Stock Prices and Social Dynamics," *Brookings Papers on Economic Activity*, 1984:2, 457-510.
- Shiller, Robert J., 2014. "Speculative Asset Prices," *American Economic Review*, 104, no. 6 (June), 1486-1517.
- Summers, Lawrence H., 1986. "Does the Stock Market Rationally Reflect Fundamental Values?" *Journal of Finance*, 41, no. 3 (July), 591-601.
- Wachter, Jessica A., 2013. "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?" *Journal of Finance*, 68, no. 3, 987-1035.

Table 1: Percent of EMV Articles in Each Category, 1985-2017

Panel A. General Economic Categories	Percent of EMV Articles	
Macroeconomic News and Outlook	72.3	
Commodity Markets	43.7	
Interest Rates	30.7	
Financial Crises	8.1	
Exchange Rates	2.0	
Healthcare Matters	6.4	
Litigation Matters	4.7	
Competition Matters	3.8	
Labor Disputes	4.0	
Intellectual Property Matters	3.3	
Panel B. Policy-Related Categories	Percent of EMV Articles	Percent of EPU Articles
Fiscal Policy:	34.7	44.6
Taxes	29.8	36.1
Government Spending, Deficits, and Debt	6.1	15.3
Entitlement and Welfare Programs	7.1	12.0
Monetary Policy	29.5	34.9
Regulation (generic regulation + 4 big regulation categories)	24.9	27.1
Financial Regulation	14.7	6.3
Competition Policy	2.4	1.1
Intellectual Property Policy	0.1	0.3
Labor Regulations	2.0	3.3
Immigration	0.2	1.5
Energy and Environmental Regulation	1.3	5.5
Lawsuit and Tort Reform, Supreme Court Decisions	1.4	4.2
Housing and Land Management	1.2	1.5
Other Regulation: Education, Communications, Consumer Product Safety, and more	1.0	1.7
National Security Policy	13.1	28.6
Government-Sponsored Enterprises (e.g., Fannie Mae)	4.9	2.7
Trade Policy	2.8	6.0
Healthcare Policy	3.6	8.5
Food and Drug Policy	1.3	1.0
Transportation, Infrastructure, and Public Utilities	1.3	2.6
Elections and Political Governance	3.0	8.2
Agricultural Policy	0.2	0.6

Notes: The second column reports the share of EMV articles with one or more terms in the indicated category-specific term set. See Appendix B for the term sets. The rightmost column in Panel B reports the share of EPU articles that contain one or more terms in the category-specific set, where EPU articles are those that meet the criteria of Baker, Bloom and Davis (2016) for policy-related economic uncertainty.

Table 2: Regressions of Stock Market Volatility Measures on the EMV Tracker

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	VIX _t	VIX _t	VIX _t	VIX _t	Log(VIX _t)	RVol _t	RVol _t
EMV _t	0.76 (0.06)	0.53 (0.10)	0.43 (0.08)	0.47 (0.10)		0.96 (0.09)	0.79 (0.13)
EMV _{t-1}		0.20 (0.09)		-0.12 (0.09)			
EMV _{t-2}		0.21 (0.05)		-0.02 (0.09)			
Log(EMV _t)					0.78 (0.03)		
VIX _{t-1}			0.58 (0.06)	0.67 (0.09)			
RVol _{t-1}							0.24 (0.12)
R ²	0.61	0.70	0.83	0.84	0.60	0.65	0.69
Obs.	396	394	395	394	396	396	395

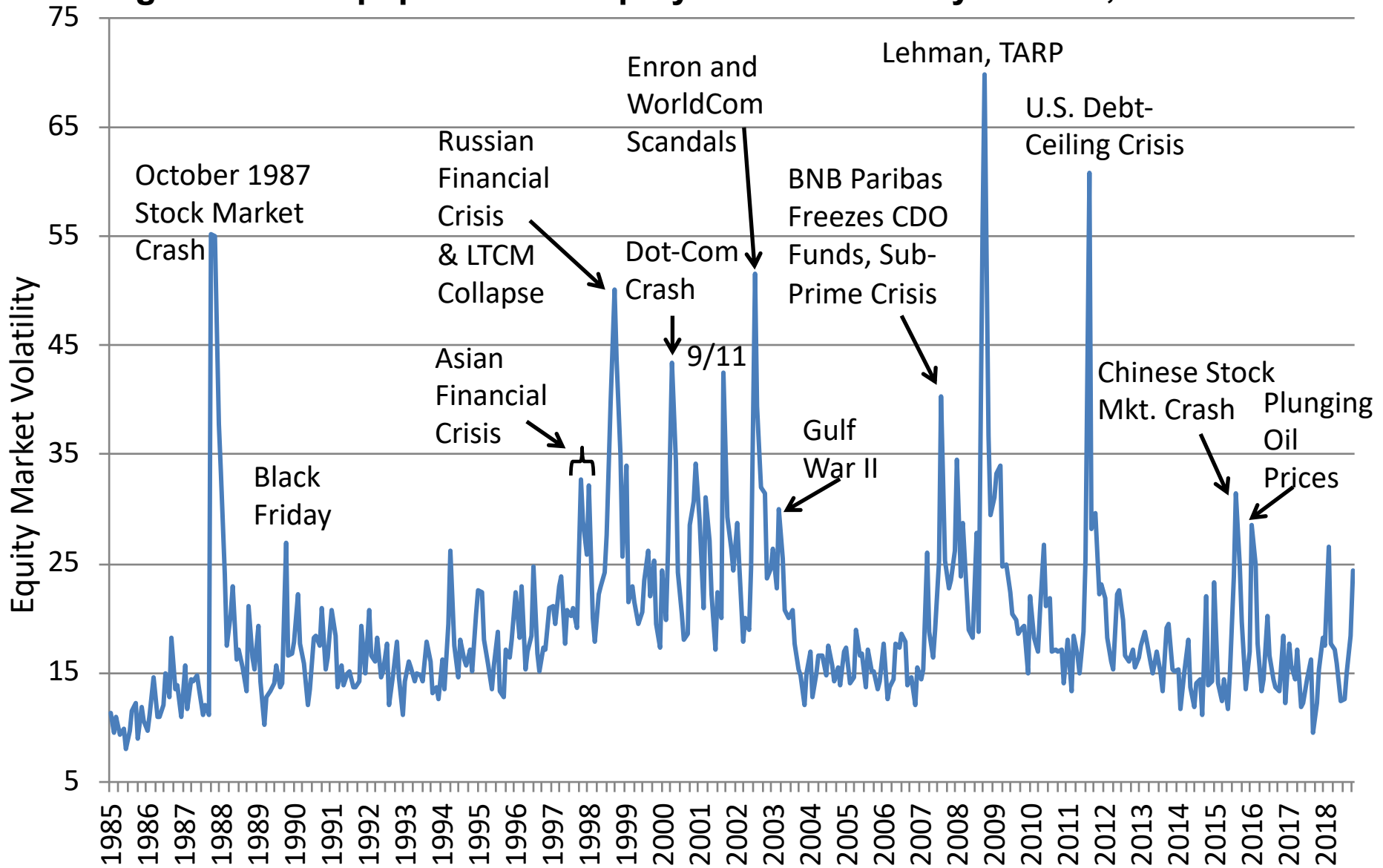
Notes: Each column reports a regression of the indicated dependent variable on the indicated row variables, using monthly data from January 1985 to December 2018. The sample for Columns (2) and (4) starts in March 1985. EMV is Equity Market Volatility tracker developed in Section 2.1. VIX is the monthly average of daily closing values on the CBOE 30-day implied volatility index from January 1990 onwards, appended to data from Berger et al. (2019) in earlier years. RVol is the standard deviation of daily returns on the S&P500 in the month. Robust standard errors in parentheses.

Table 3: Summary Statistics for the VIX, EMV and NVIX, January 1985 to March 2016

	VIX	EMV	NVIX
Standard Deviation	7.81	8.14	4.83
Skewness	2.19	2.40	1.27
Kurtosis	10.76	11.37	7.43
Pairwise Correlation with VIX		0.78	0.70
Mean Absolute Difference with VIX		3.69	4.03

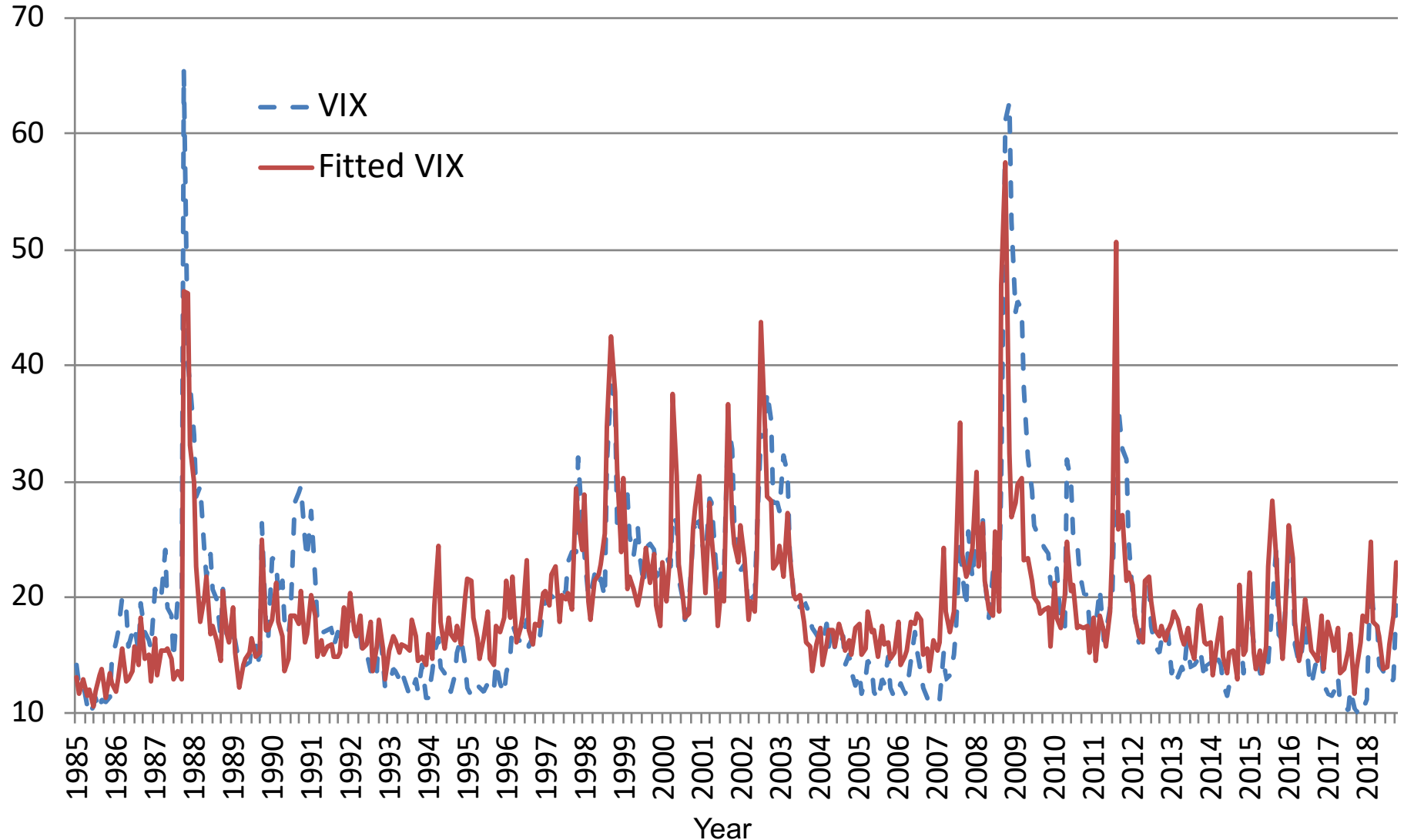
Notes: The NVIX measure developed by Manela and Moreira (2017) runs through March 2016 and is downloadable at <http://apps.olin.wustl.edu/faculty/manela/data.html>. See the notes to Table 2 for definitions of VIX and EMV. We multiplicatively scale the NVIX and EMV to match the mean value of the VIX from 1985 to 2015.

Figure 1: Newspaper-Based Equity Market Volatility Tracker, 1985-2018



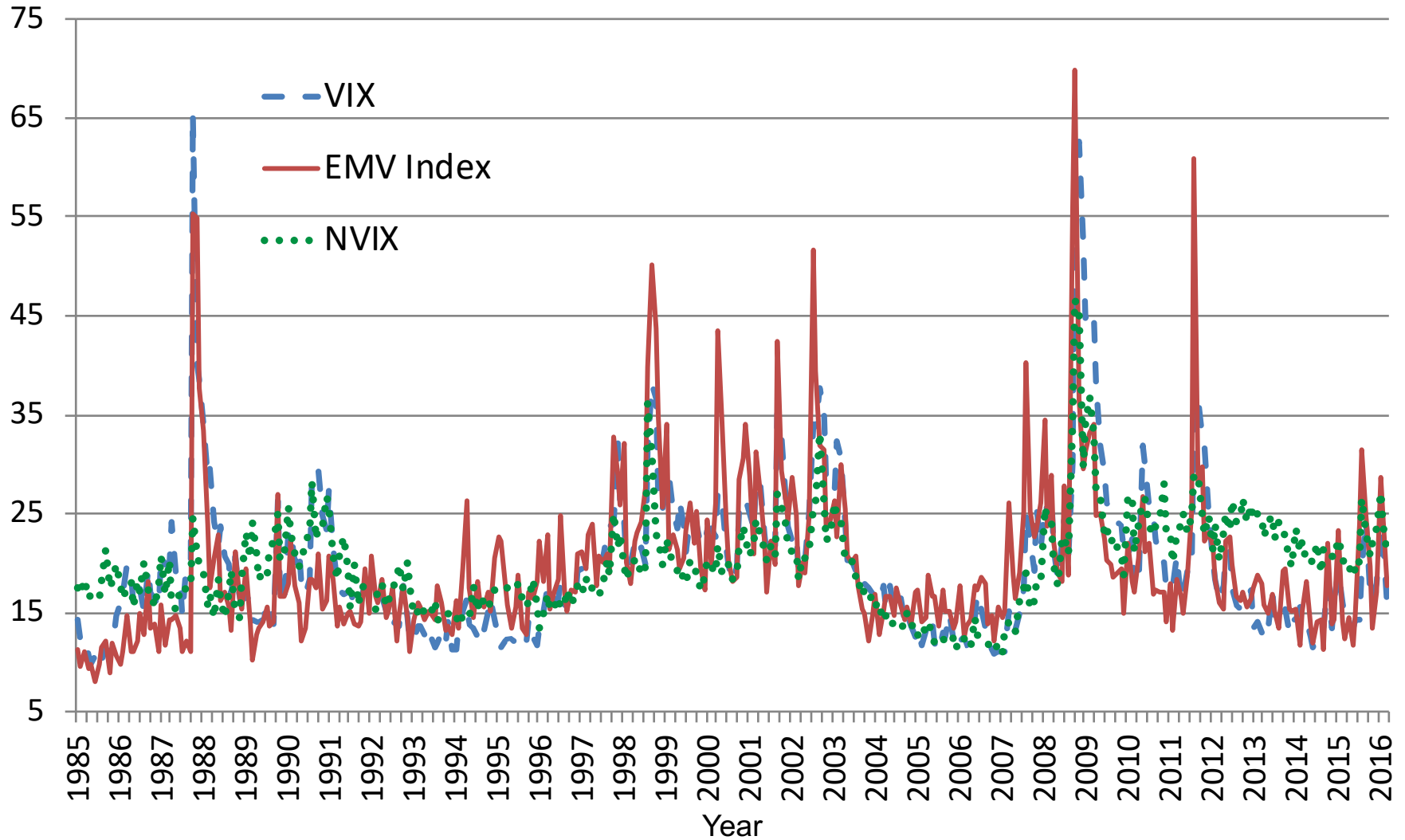
Notes: The Equity Market volatility (EMV) tracker runs from January 1985 to October 2018. We construct it using scaled frequency of articles that contain terms about Economics, the Stock Market, and Volatility in 11 leading U.S. newspapers, as detailed in Section 2.1. We scale the EMV tracker to match the mean value of the VIX from 1985 to 2015.

Figure 2: VIX and Fitted VIX from a Regression on EMV, 1985-2018



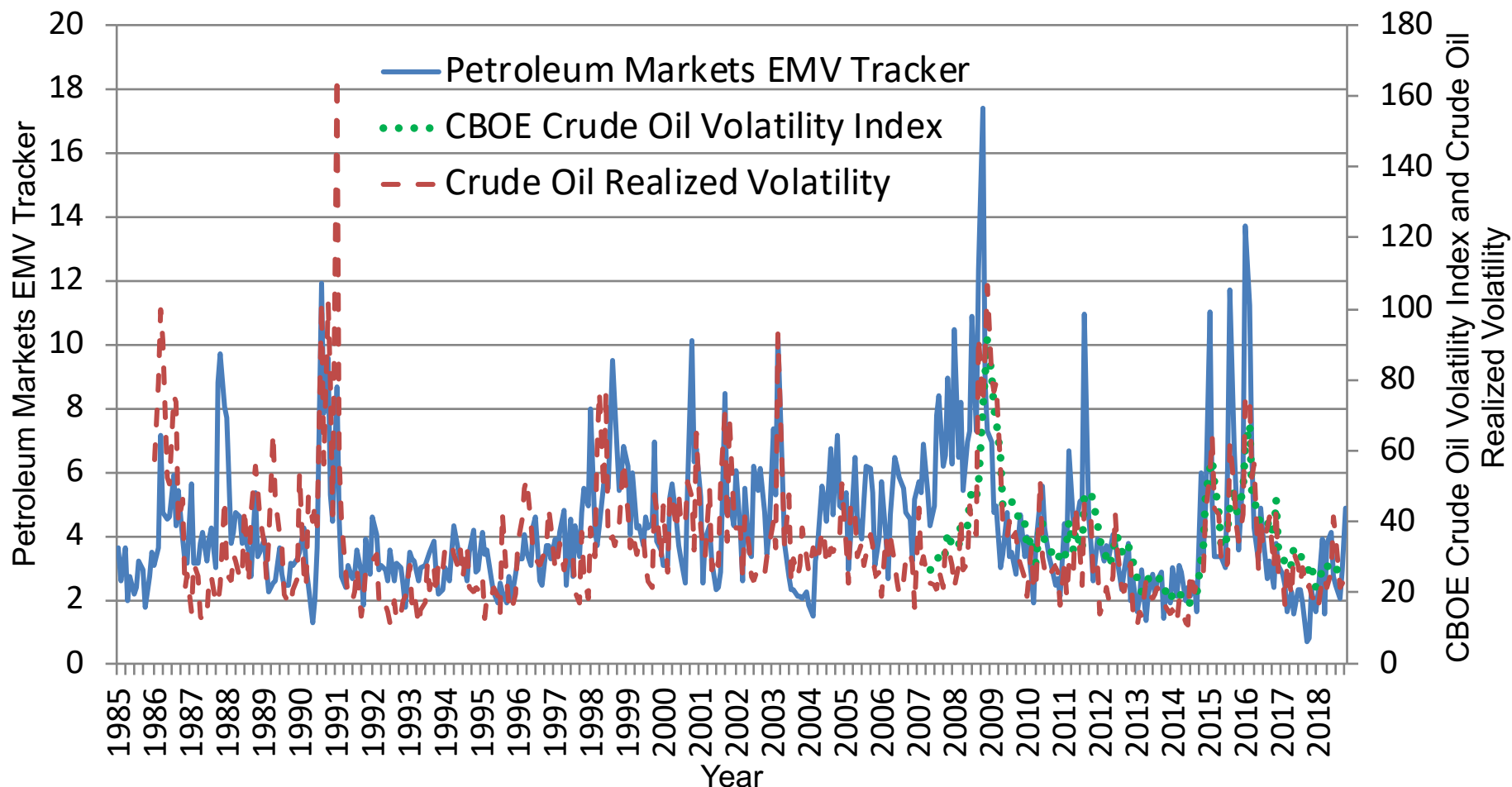
Notes: Data for the CBOE 30-Day VIX data from 1990 to 2017 appended to the VIX series in Berger et al. (2019) from 1985 to 1989. "Fitted VIX" values are from the regression VIX on EMV reported in Table 2, column (1) Both series run from January 1985 to October 2018. ²³

Figure 3: VIX, EMV and NVIX, January 1985 to March 2016



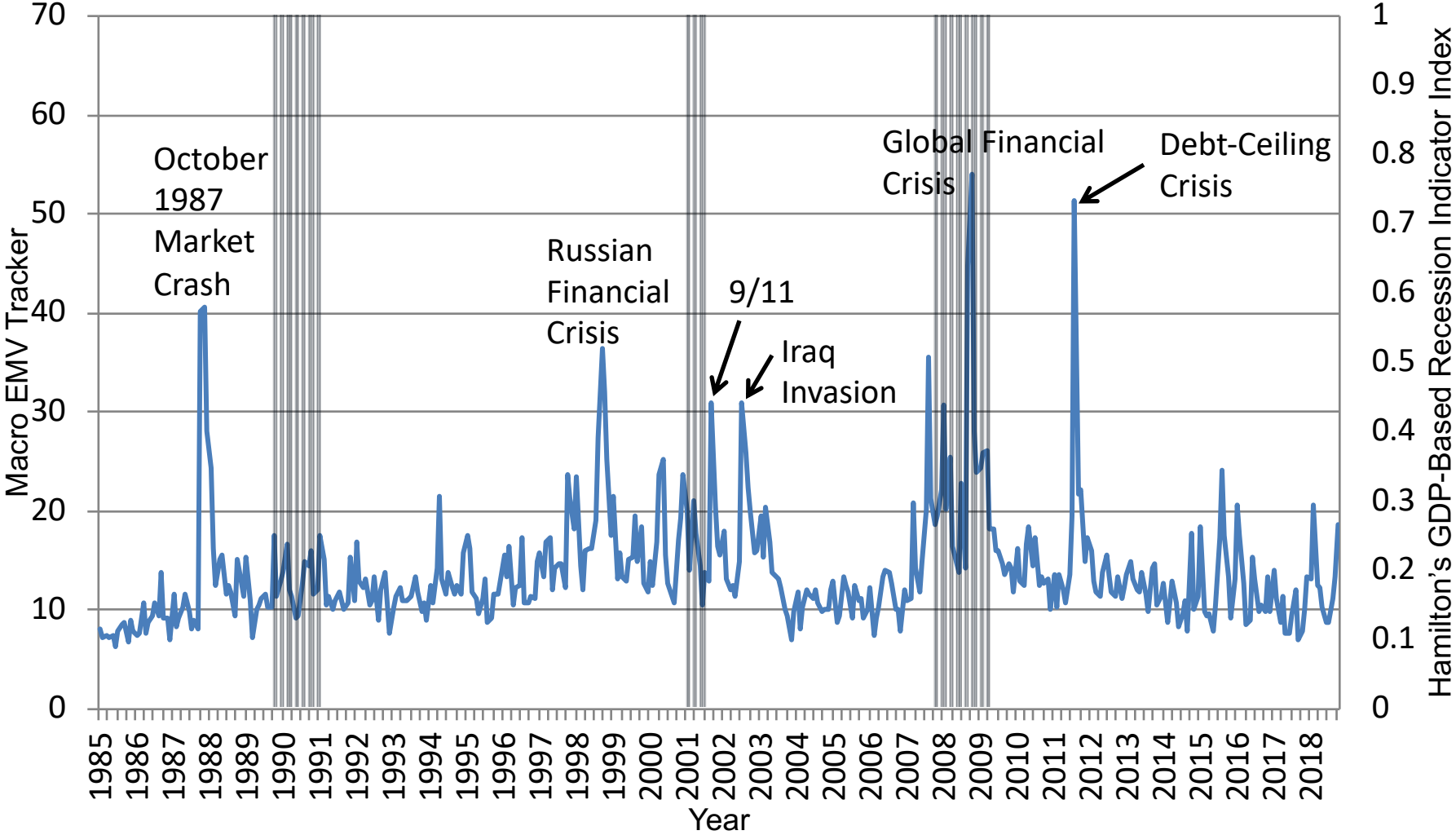
Notes: The NVIX measure is from Manela and Moreira (2017) and runs through March 2016. See the notes to Figure 2 for the VIX and NVIX.. We multiplicatively scale NVIX and EMV to match the mean value of the VIX from 1985 to 2015.

Figure 4: Petroleum Markets EMV Compared to Oil Price Volatility, Monthly, 1985 to 2018



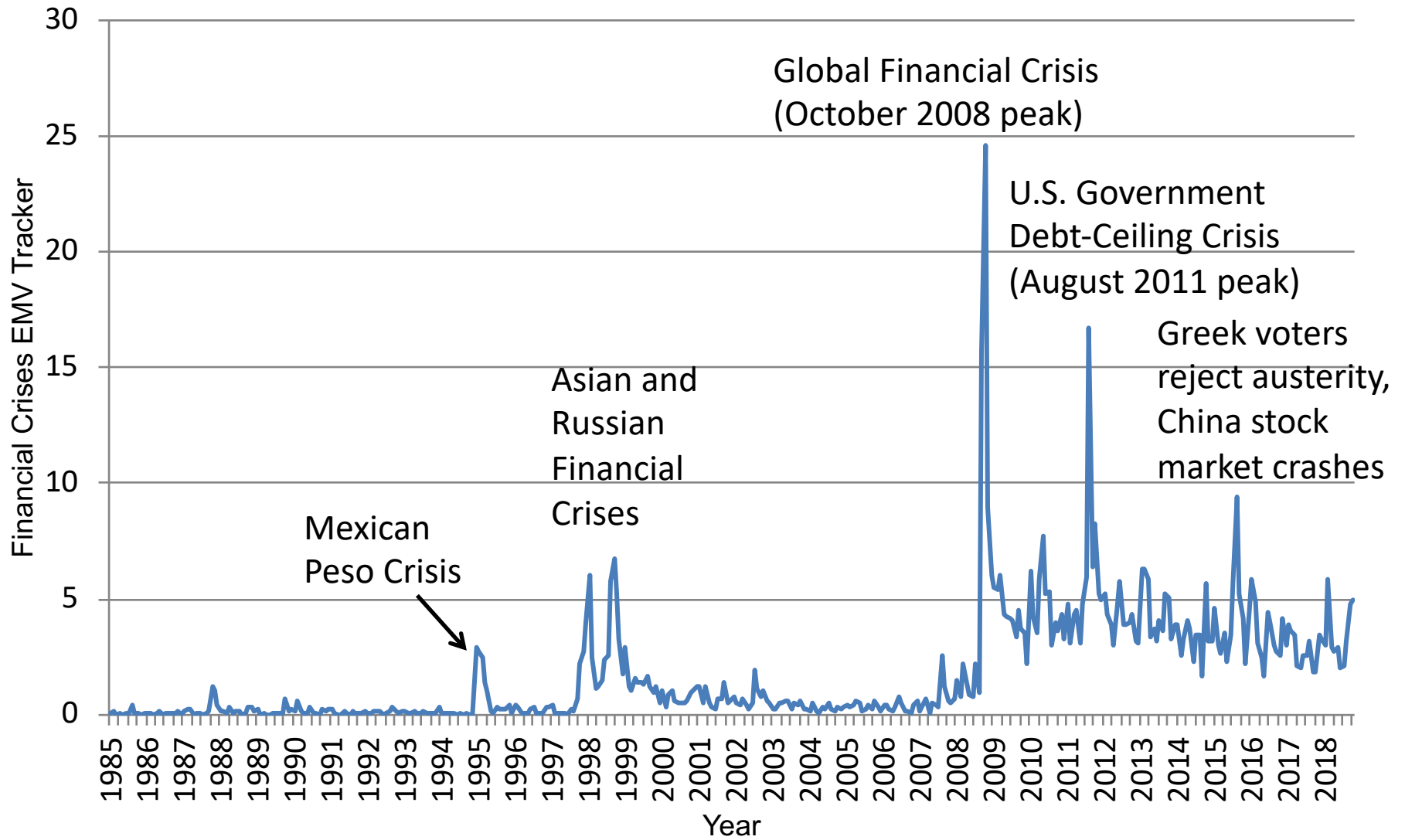
Notes: CBOE Crude Oil Volatility Index is the monthly mean of daily CBOE Crude Oil ETF Volatility Index values. Crude Oil Realized Volatility reflects daily price data for West Texas Intermediate. We extract both series from the St. Louis Federal Reserve FRED database. The Petroleum Markets EMV tracker is constructed from scaled frequency counts of newspaper articles. See Sections 2.1 and 3.4 in the text for details.

Figure 5: Macroeconomics EMV Tracker



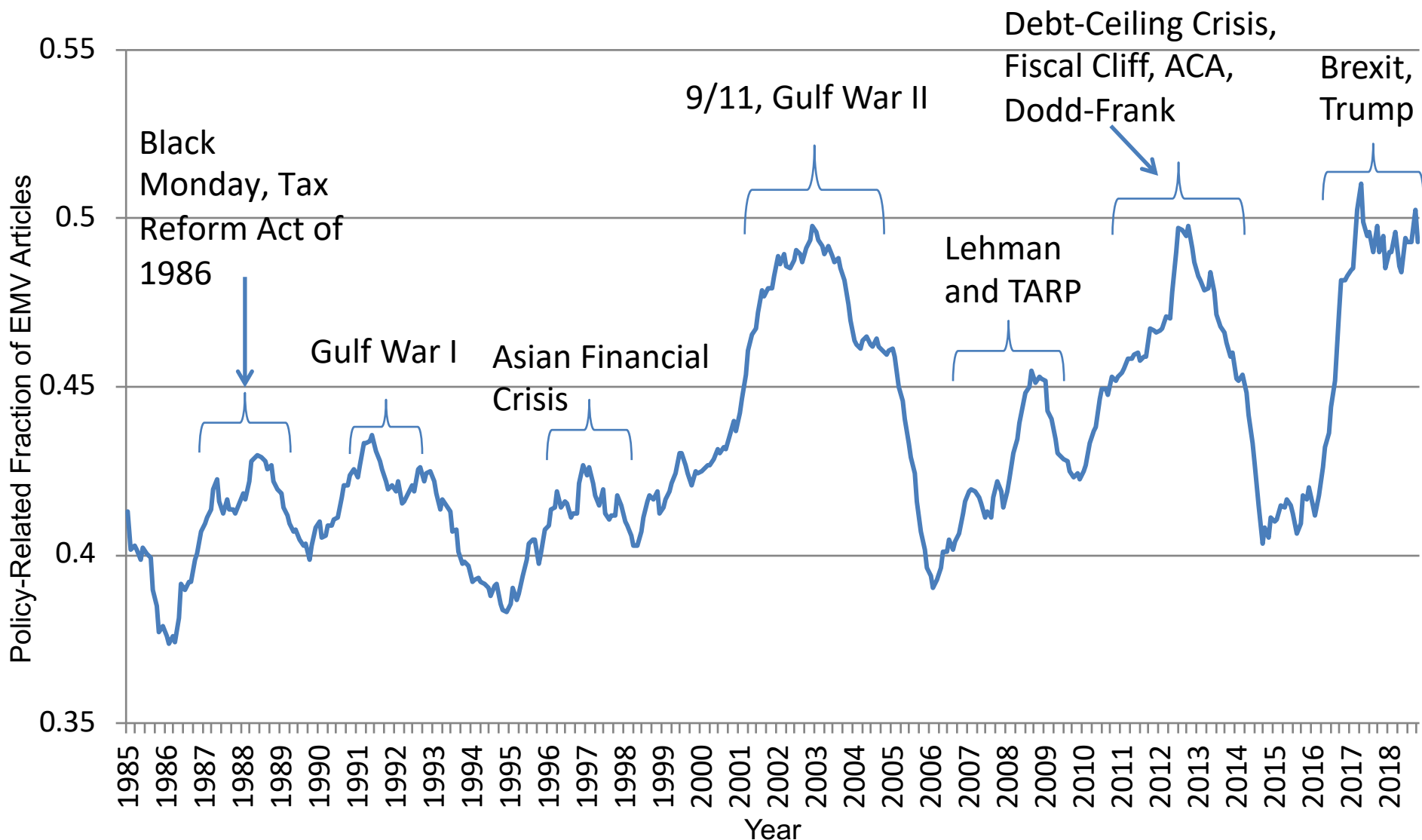
Notes: We construct the Macroeconomics EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Macroeconomic News and Outlook**. See Appendix B for the list of terms.

Figure 6: Financial Crisis EMV Tracker, 1985-2018



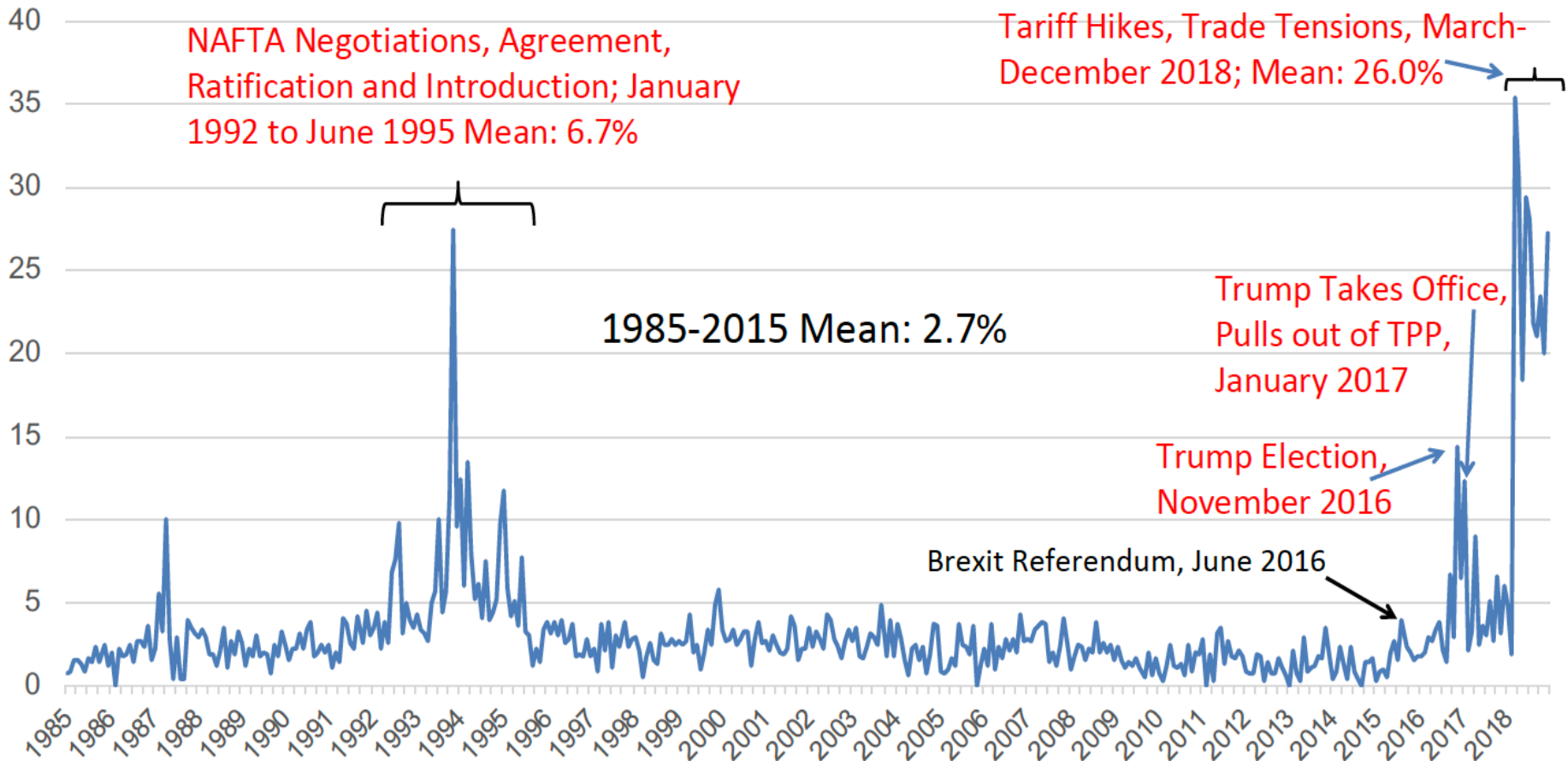
Notes: We construct the Financial Crisis EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Financial Crises**. See Appendix B for the list of terms.

Figure 7: Fraction of EMV Articles that Discuss Policy Matters, 12-Month Moving Average, 1985-2018.



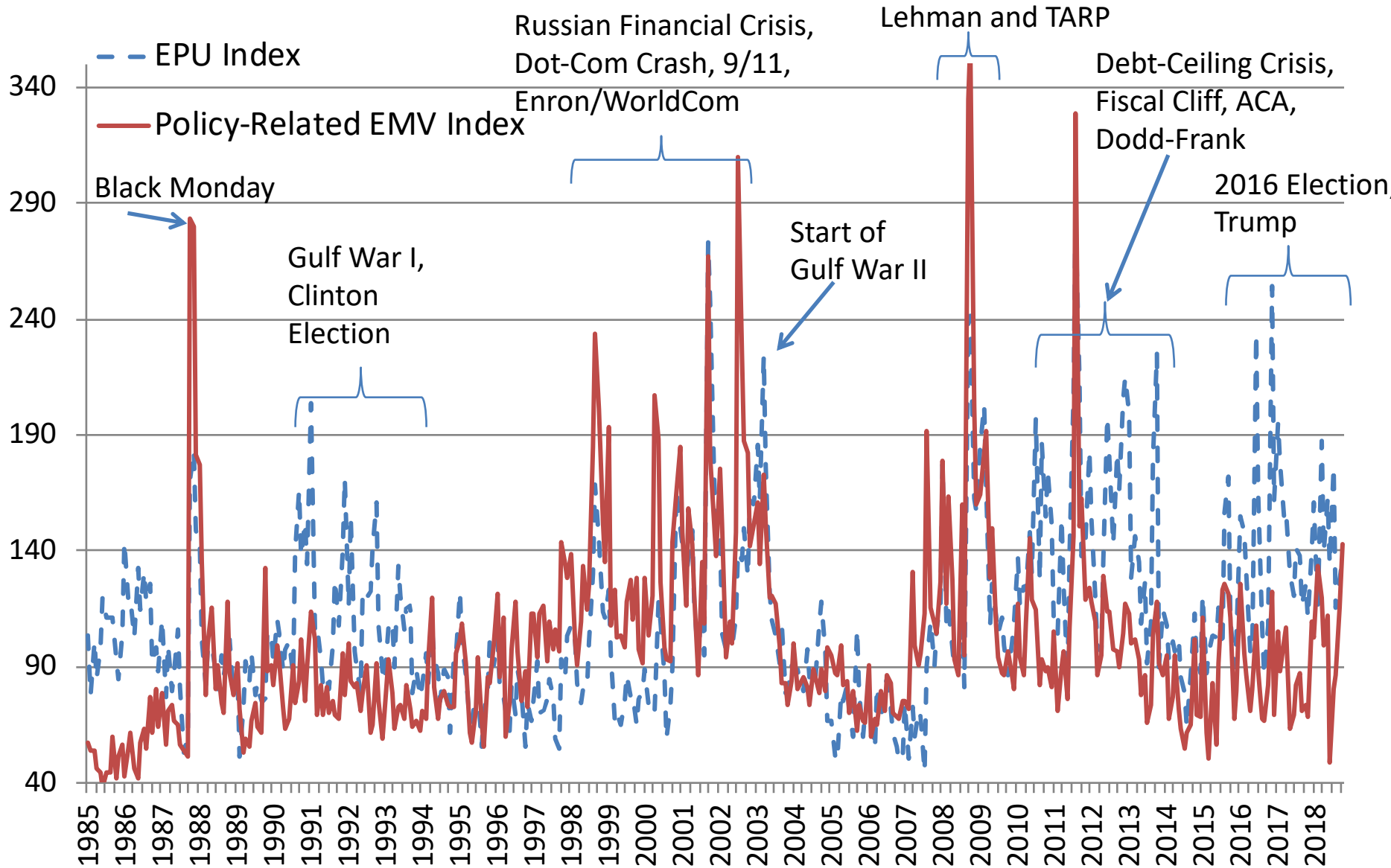
Notes: We sum EMV article counts over policy-related categories and divide by the sum of EMV article counts over all categories (general and policy-related). We compute this ratio for each newspaper and month, average over papers by month and then compute a moving average with six lags and leads, truncating lags (leads) near the sample start (end).

Figure 8: Percent of EMV Articles that Discuss Trade Policy Matters, January 1985 to December 2018



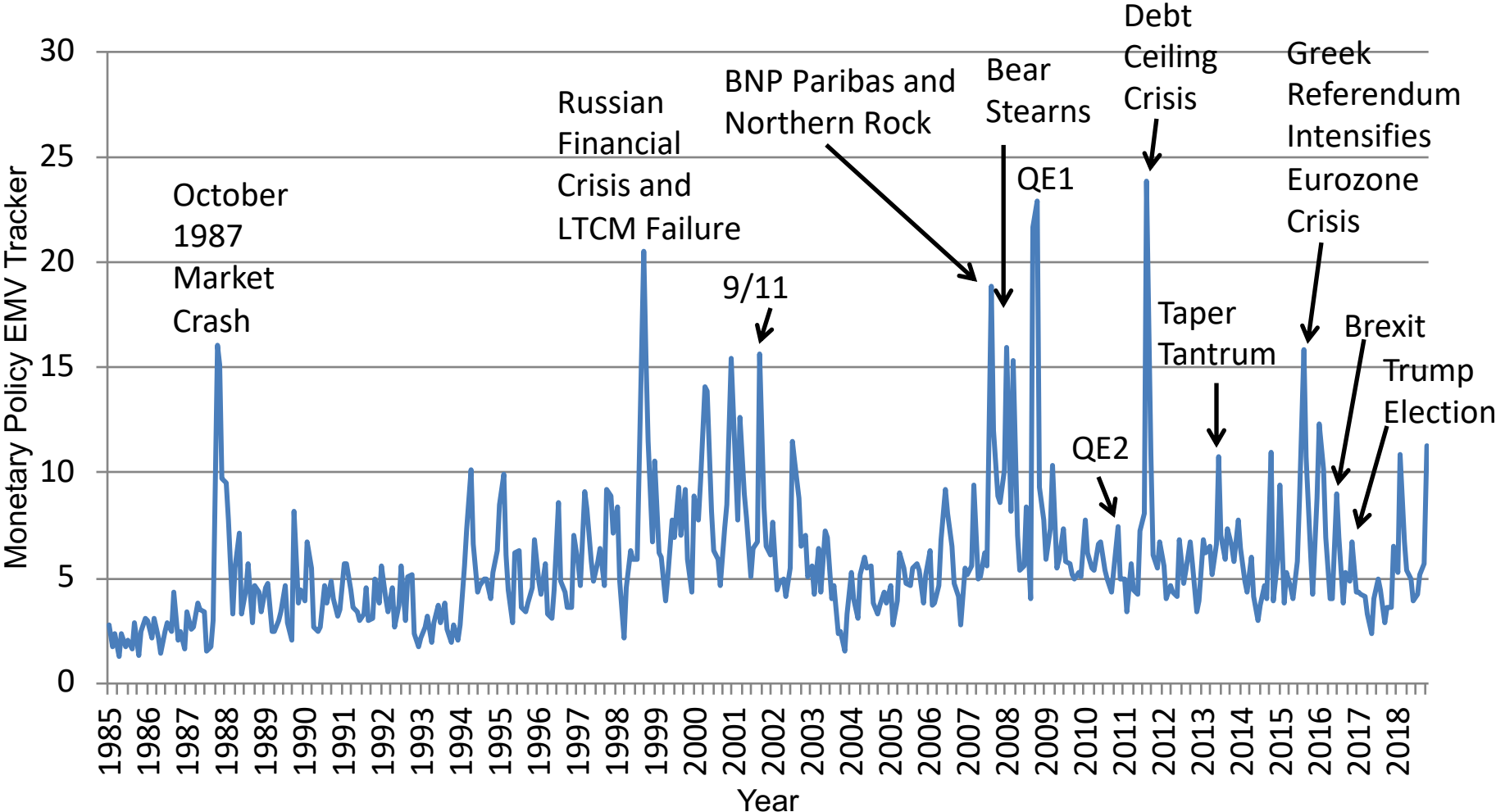
Note: This chart shows the percent of EMV articles that contain one more terms in **Trade Policy** by month. See Appendix B for a specification of the terms in **Trade Policy**.

Figure 9: Policy-Related EMV Tracker and BBD EPU Index, 1985-2018



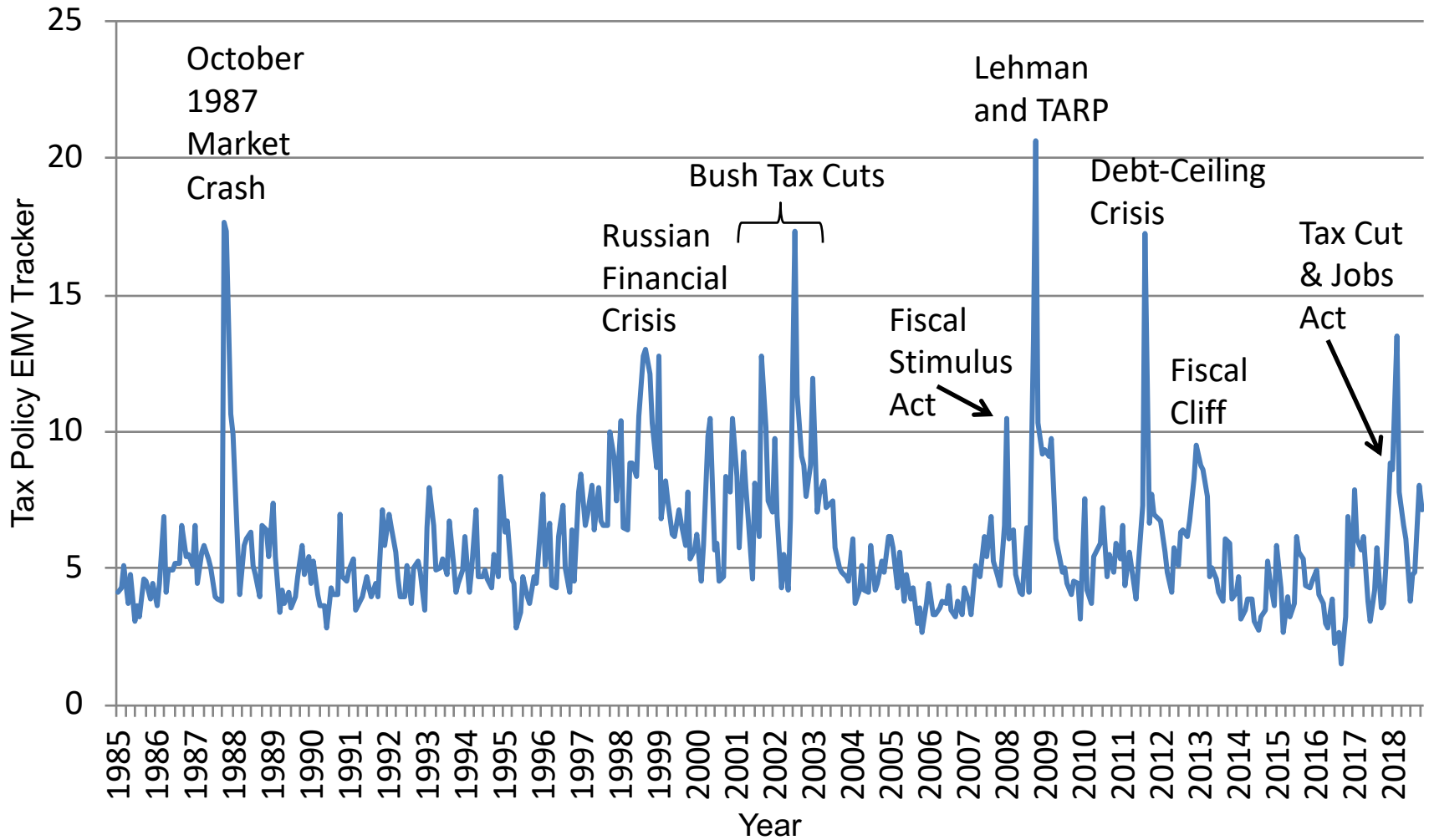
Notes: The BBD EPU Index is from Baker Bloom and Davis (2016). To construct the Policy-Related EMV tracker, we multiply our overall EMV tracker by the fraction of EMV articles the discuss policy matters. We multiplicatively rescale Policy-Related EMV to match mean of the BBD EPU Index from 1985 to 2009.

Figure 10: Monetary Policy EMV Tracker, 1985-2018



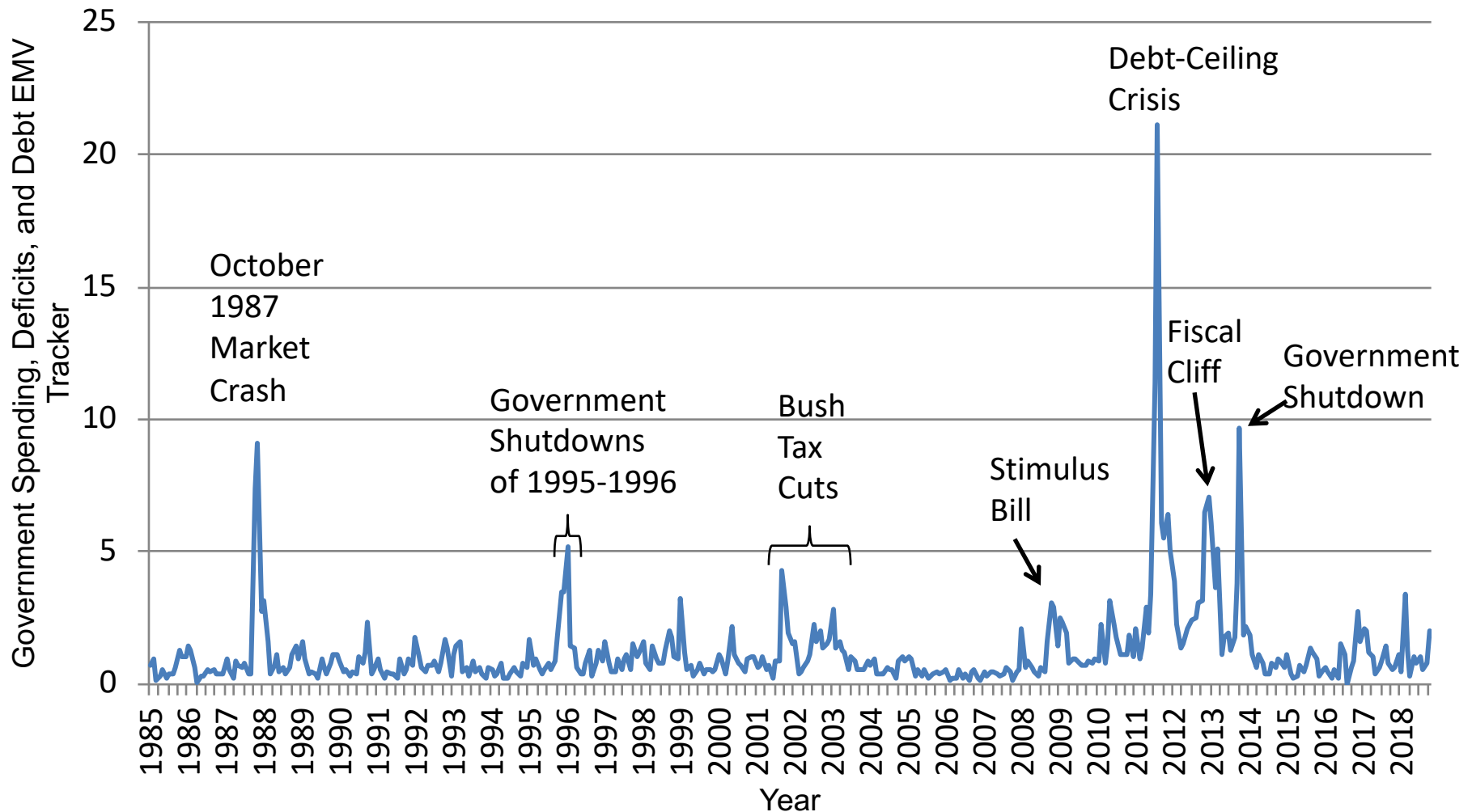
Notes: We construct the Monetary Policy EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Monetary Policy**. See Appendix B for the list of terms.

Figure 11: Tax Policy EMV Tracker, 1985-2018



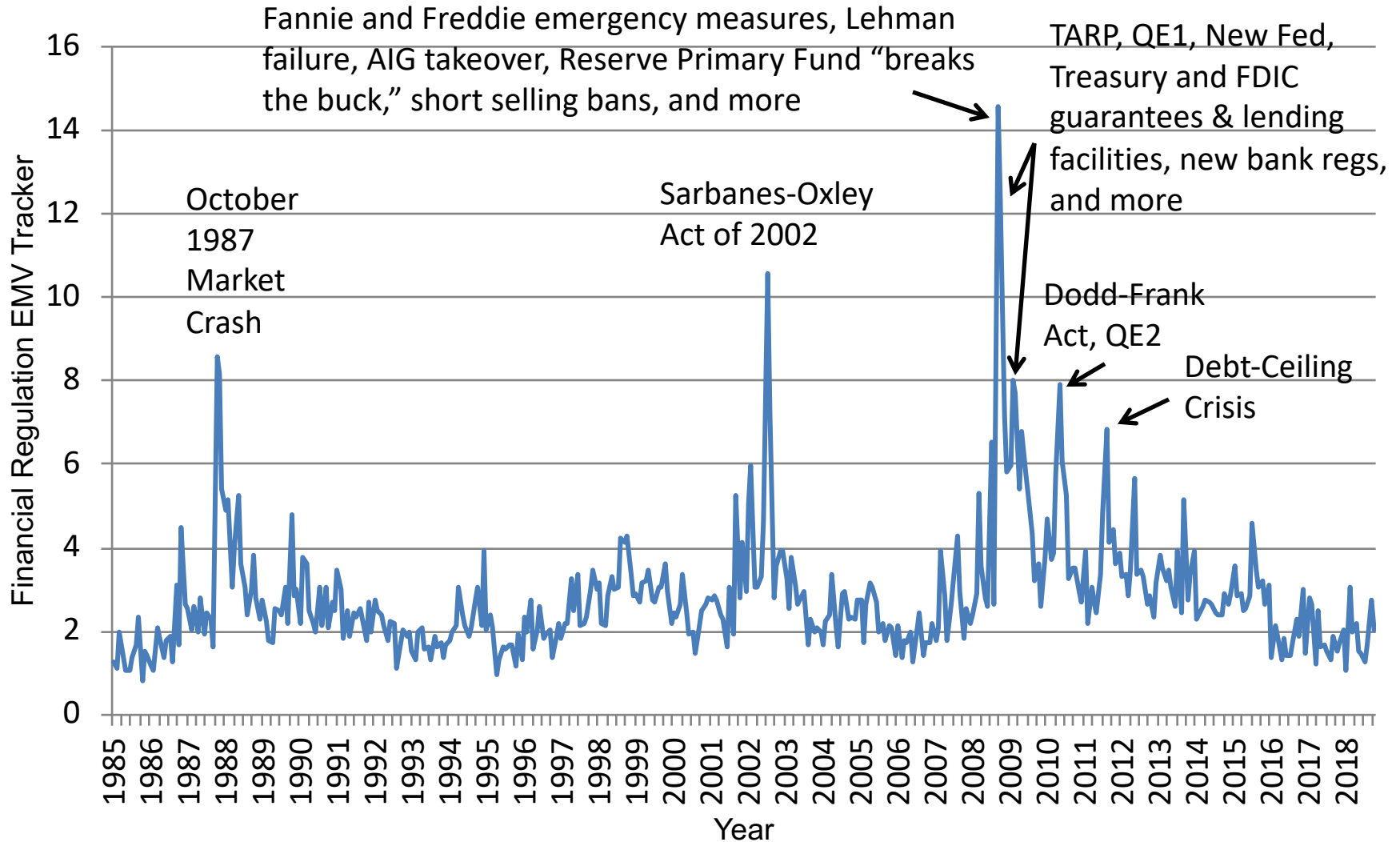
Notes: We construct the Tax Policy EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Taxes**. See Appendix B for the list of terms.

Figure 12: Government Spending, Deficits and Debt EMV Tracker, 1985-2018



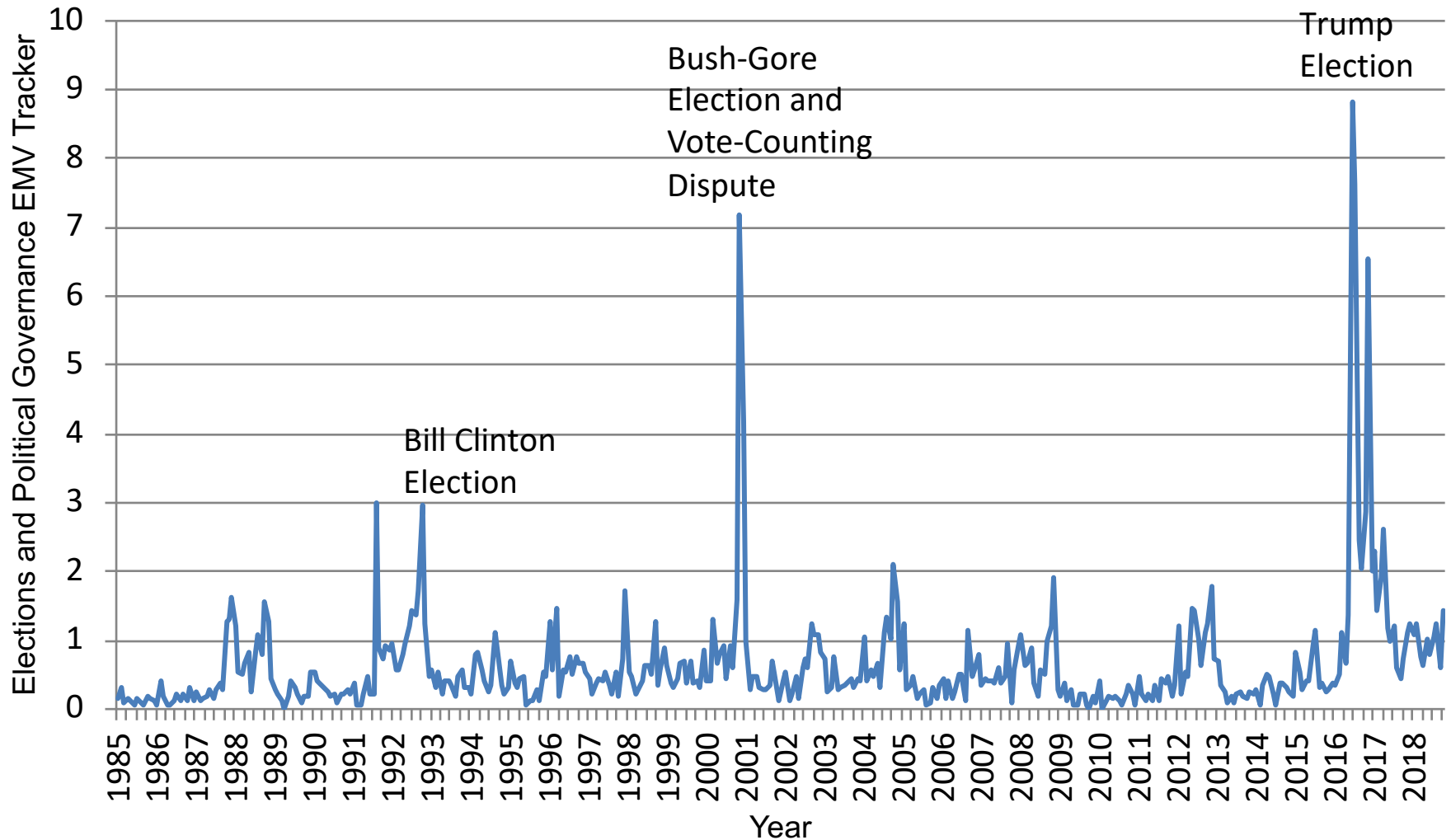
Notes: We construct the Government Spending, Deficits and Debt EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Government Spending, Deficits and Debt**. See Appendix B for the list of terms.

Figure 13: Financial Regulation EMV Tracker, 1985-2018



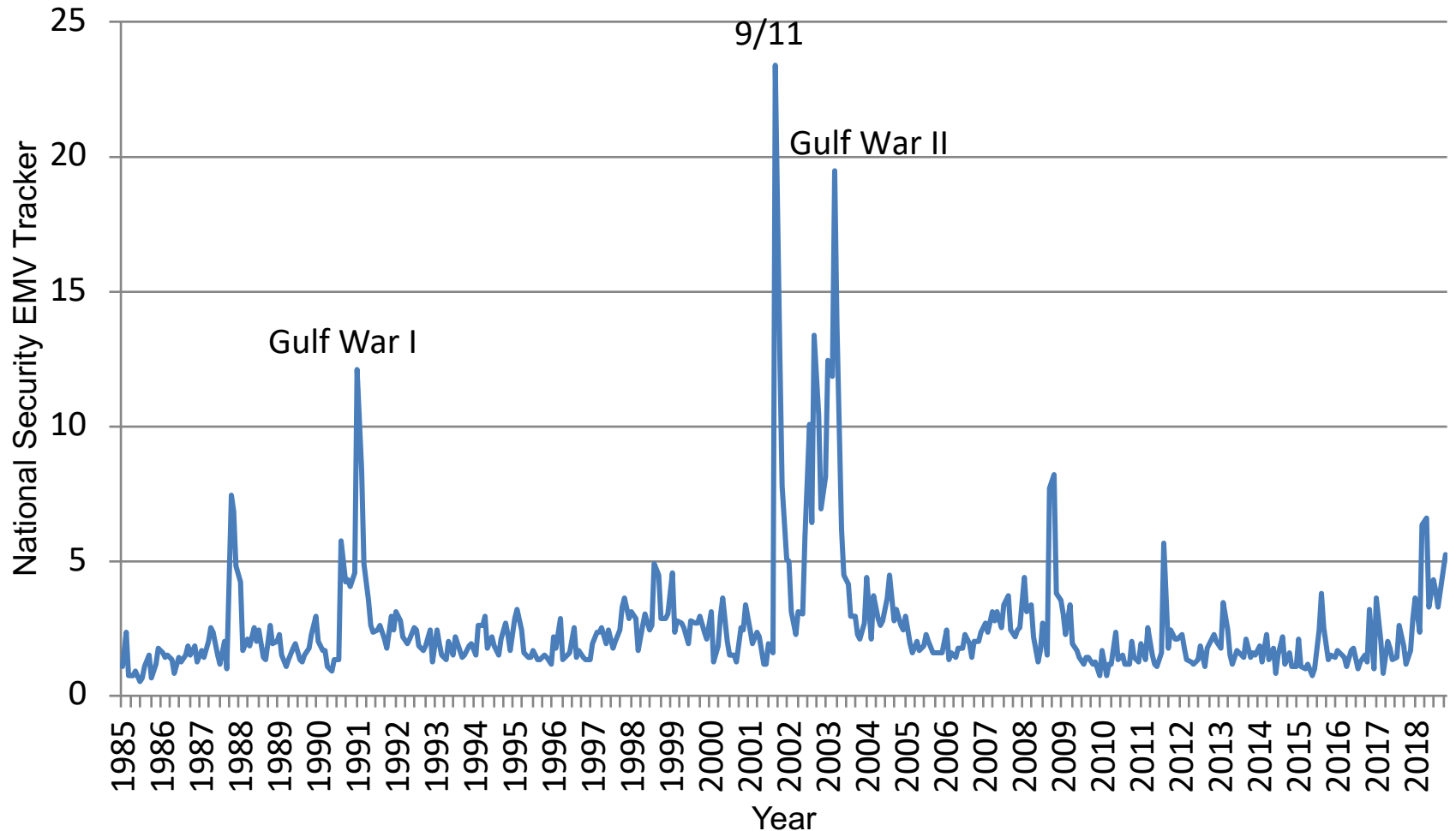
Notes: We construct the Financial Regulation EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Financial Regulation**. See Appendix B for the list of terms.

Figure 14: Elections and Political Governance EMV Tracker, 1985-2018



Notes: We construct the Elections and Political Governance EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Elections and Political Governance**. See Appendix B for the list of terms.

Figure 15: National Security EMV Tracker, 1985-2018



Notes: We construct the National Security EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **National Security**. See Appendix B for the list of terms.

Appendix A. Additional Information About Our Text Sources

Figure A.1 plots the total number of articles in the newspapers we draw on in constructing our Equity Market Volatility (EMV) tracker and related measures. The total article counts fluctuate in the range of 60-90 thousand per month in the first 16 years of our sample period, then drift down, reaching lows of about 35,000 per month.

The rightmost column of Table A.1 reports average daily article counts by newspaper from 1985 to 2017. The remaining columns report average daily counts and percentages of all articles that satisfy various criteria defined by our **E**, **M** and **V** term sets. Not surprisingly, the *Wall Street Journal* stands out for percent of articles devoted to topics encompassed by our term sets.

Five newspapers are not available to us for the entire 1985-2018 time period. Access World News discontinued coverage of the *Dallas Morning News* from July 2016. The ProQuest newspaper archive covers the *New York Times* through 2015 only, as of this writing. Access World News coverage of *USA Today* from Access World News is missing in 1985, 1986 and the first half of 1987. roquest archive coverage of the *Houston Chronicle* is missing for most of 1985, and its coverage of the *Washington Post* is missing in 1985 and 1986.

When missing, we impute scaled counts using fitted values from the regressions,

$$SC_{jt} = \alpha^j + \sum_{i \in N^*} \beta_i^j SC_{it} + \varepsilon_{it}^j, \quad \text{for } j \in N^{Miss}$$

where N^* is the set of newspapers with complete coverage (*Boston Globe*, *Chicago Tribune*, *Los Angeles Times*, *Miami Herald*, *San Francisco Chronicle*, and *Wall Street Journal*), N^{Miss} is the set of newspapers with missing coverage, and SC_{it} is the scaled EMV frequency count for newspaper i in month t . We run this regression from 1988 to 2015 for each paper ion N^{Miss} and use it to impute missing SC_{jt} values in other months.

Table A1: Articles per Day by Term Set Category, 1985-2017

	Articles in Set E		Articles in $E \cap V$		Articles in $E \cap M$		Articles in $E \cap M \cap V$		All Articles per Day
	Per Day	Percent	Per Day	Percent	Per Day	Percent	Per Day	Percent	
Dallas Morning News	19.33	11.3	2.24	1.3	1.39	0.8	0.38	0.22	171.2
Houston Chronicle	18.97	11.2	2.31	1.4	1.50	0.9	0.38	0.23	169.6
Miami Herald	20.03	10.6	2.23	1.2	1.30	0.7	0.33	0.18	189.5
San Francisco Chronicle	12.44	13.2	1.56	1.7	1.02	1.1	0.26	0.28	94.1
USA Today	18.35	13.5	2.89	2.1	2.18	1.6	0.70	0.51	135.8
Boston Globe	20.75	14.0	3.14	2.1	1.64	1.1	0.51	0.35	147.9
Chicago Tribune	27.43	9.7	4.29	1.5	2.74	1.0	0.92	0.32	283.9
Wall Street Journal	44.17	39.7	10.58	9.5	9.53	8.6	3.62	3.25	111.3
New York Times	54.32	13.4	9.67	2.4	6.93	1.7	2.16	0.54	412.0
Los Angeles Times	48.90	17.8	6.75	2.5	3.60	1.3	1.14	0.41	274.8
Washington Post	41.34	20.4	7.34	3.6	3.66	1.81	1.18	0.58	202.6

Notes: See main text, Section 2.1 for definitions of the E , M and V term sets. The last column reports articles per day based on a count of weekdays per year. The Dallas Morning News coverage stops in May 2016, the New York Times coverage stops at the end of 2015, the USA Today coverage begins in the middle of 1987, the Houston Chronicle coverage begins near the end of 1985, and the Washington Post coverage begins in 1987, so the days are adjusted for those newspapers.

Appendix B. Category-Specific Term Sets

Our term sets for the Policy-Related Categories build on Baker, Bloom and Davis (2016) and Davis (2017). We developed terms sets for the General Economic Categories for this paper. We group related terms into topics within categories, as indicated by { }. These topical groupings play no role in counting methods or analysis, but we find them helpful in conceptualizing the boundaries of each category. In defining our **Regulation** term set, we hit a ceiling on the number of terms per search query. Given this constraint, we limit our **Regulation** term set to the union of terms in the most common regulation categories plus a few generic terms indicative of government regulation.

General Economic Categories

- **Macroeconomic News and Outlook:** {gold, silver}, {gdp, economic growth}, {depression, recession, economic crisis}, {macroeconomic indicators, macroeconomic news}, {rail loadings, railroad loadings}, {cpi, inflation, consumer prices, ppi, producer prices}, {housing prices, home prices, homebuilding, homebuilders, housing starts, home sales, building permits, residential sales, mortgages, residential construction, commercial construction, commercial real estate, real estate}, {labor force, workforce, unemployment, employment, unemployment insurance, ui claims, jobs report, jobless claims, payroll, underemployment, quits, hires, weekly hours}, {wages, labor income, labor earnings}, {corporate bonds, bank loans, interest rates}, {trade news, trade surplus, trade deficit, national exports, national imports}, {business investment, business inventories}, {consumer spending, retail sales, consumer purchases}, {consumer confidence, consumer sentiment, macro outlook, business sentiment, business confidence}, {industrial production, ism report, manufacturing index}, {household credit, household savings, household debt, household borrowing, consumer credit}
- **Commodity Markets:** {wheat, corn, soy, sugar, cotton, beef, pork}, {oil, coal, natural gas}, {biofuel, ethanol}, {steel, copper, zinc, tin, platinum, rare earth metals, gold, metal, silver, aluminum, lead}, {cme, commodity exchange, cbot, nymex, lme, London metal exchange, mercantile exchange, intercontinental exchange, board of trade}, {keystone pipeline, Alaska pipeline, oil pipeline, gas pipeline}
- **Interest Rates:** {interest rates, yield curve, fed funds rate, overnight rate, repo rate, T-bill rate, bond rate, bond yield}
- **Financial Crises:** {financial crisis, financial crises}, {Northern Rock failure, Lehman failure, Lehman Brothers failure, AIG Takeover}, {euro crisis, Eurozone crisis, Greek crisis}
- **Exchange Rate:** {exchange rate}, {currency crisis}, {currency devaluation, currency depreciation}, {currency revaluation, currency appreciation}, {crawling peg, managed float}, {currency manipulation, currency intervention}
- **Healthcare Matters:** {healthcare}, {health insurance}, {Medicaid}, {Medicare}, {Affordable care act, Obamacare}, {medical liability, medical malpractice}, {prescription drug}, {drug policy}, {food and drug administration, fda}, {VA hospital, VA healthcare, Veterans Affairs hospital, Veterans Affairs healthcare, Veterans Health Administration}, {National Institutes of Health}
- **Litigation Matters:** {lawsuit, litigation, class action, tort}, {punitive damages}, {patent infringement, trademark infringement, copyright infringement}, {medical malpractice}, {Supreme Court}

- **Competition Matters:** {antitrust, competition policy, competition law}, {federal trade commission, ftc}, {unfair business practice}, {monopoly, monopolization}, {cartel}, {price fixing, price conspiracy}, {Sherman Act}, {Robinson Patman Act}, {Clayton Act}, {Hart-Scott-Rodino}, {European Commission}
- **Labor Disputes:** {labor dispute, labor unrest, strike}, {labor litigation, employee discrimination, wage and hour litigation, labor class action}
- **Intellectual Property Matters:** {patent}, {trademark}, {copyright}, {Patent and Trademark Office}, {International Trade Commission}, {federal trade commission, ftc}, {intellectual property}, {Hatch-Waxman}, {new drug application}

Policy-Related Categories

- **Fiscal Policy: Taxes ∪ Government Spending, Deficits and Debt ∪ Entitlement and Welfare Programs**
 - **Taxes:** {taxes, tax, taxation, taxed}, {income tax, tax on individuals, personal tax}, {capital gains tax, tax on capital gains}, {dividend tax}, {mortgage interest deduction, deduction for mortgage interest}, {IRA account, Roth IRA, traditional IRA, 401-k}, {state and local tax deduction, deductibility of state and local tax}, {payroll tax, social security tax, social security contributions, Medicare taxes, FICA, unemployment tax, FUTA}, {sales tax, excise tax, value added tax, vat, goods and services tax, gross receipts tax}, {carbon tax, energy tax}, {corporate tax, business tax, profit tax}, {investment tax credit, accelerated depreciation}, {R&D tax credit, research and development tax credit}, {tax credit for low-income housing, low-income housing credit}, {black liquor tax credit, black liquor credit}, {ethanol credit, ethanol credit, ethanol tax rebate}, {biofuel tax credit, biofuel producer tax credit, fuel excise tax rebate, fuel tax credit, alcohol fuel credit}, {property tax}, {fiscal cliff}, {Internal Revenue Service}
 - **Government Spending, Deficits and Debt:** {government spending, government outlays, government appropriations, government purchases}, {defense spending, military spending, defense purchases, military purchases, defense appropriations}, {entitlement spending}, {government subsidy}, {fiscal stimulus}, {government deficit}, {federal budget, government budget}, {Gramm Rudman, balanced budget, balance the budget, budget battle, debt ceiling}, {fiscal cliff, government sequester, budget sequestration, government shutdown}, {sovereign debt}
 - **Entitlement and Welfare Programs:** {entitlement program, entitlement spending, government entitlements}, {social security, Supplemental Security Income, ssi, disability insurance}, {Medicaid}, {Medicare}, {supplemental nutrition assistance program, food stamps, wic program}, {unemployment insurance, unemployment benefits, TAA program}, {welfare reform, aid to families with dependent children, afdc, temporary assistance for needy families, tanf, public assistance}, {earned income tax credit, eitc}, {head start program, early childhood development program}, {affordable housing, section 8, housing assistance, government subsidized housing}
- **Government-Sponsored Enterprises and Related Agencies:** {Federal Home Loan Mortgage Association, Freddie Mac}, {Fannie Mae, Federal National Mortgage Association}, {Federal Housing Finance Agency}, {Federal Housing Agency}, {Sallie Mae, Student Loan Marketing Association}, {Government National Mortgage Association, Ginnie Mae}, {Federal Home Loan Bank}, {Federal Farm Credit Bank, Federal Agricultural Mortgage Corporation, Farmer Mac}, {Resolution Funding Corporation, REFCORP}

- **Monetary Policy:** {monetary policy}, {money supply, open market operations}, {fed funds rate}, {discount window}, {quantitative easing}, {forward guidance}, {interest on reserves}, {taper tantrum}, {Fed chair, Greenspan, Bernanke, Volker, Yellen, Draghi, Kuroda, Jerome Powell}, {lender of last resort}, {central bank}, {federal reserve, the fed}, {European Central Bank, ecb}, {Bank of England}, {bank of japan}, {people's bank of china, pboc, pbc, central bank of china}, {Bank of Italy}, {Bundesbank}
- **Regulation:** {regulation, regulatory, regulate} ∪ **Financial Regulation ∪ Competition Policy ∪ Labor Regulations ∪ Lawsuit And Tort Reform, Supreme Court Decisions**
 - **Financial Regulation:** {bank supervision}, {thrift supervision}, {financial reform}, {truth in lending}, {firrea}, {Glass-Steagall}, {Sarbanes-Oxley}, {Dodd-frank}, {tarp, Troubled Asset Relief Program}, {Volcker rule}, {Basel}, {capital requirement}, {stress test}, {deposit insurance, fdic}, {federal savings and loan insurance corporation, fslic}, {office of thrift supervision, ots}, {comptroller of the currency, occ}, {commodity futures trading commission, cftc}, {Financial Stability Oversight Council}, {house financial services committee}, {securities and exchange commission, sec}, {Bureau of Consumer Financial Protection, Consumer Financial Protection Bureau, CFPB}, {SBA loan program}
 - **Competition Policy:** {antitrust policy, competition policy, competition law}, {federal trade commission, ftc}, {Sherman Act}, {Robinson Patman Act}, {Clayton Act}, {Hart-Scott-Rodino}, {European Commission}
 - **Intellectual Property Policy:** {patent policy, patent law}, {trademark policy, trademark law}, {copyright law}, {Patent and Trademark Office}, {International Trade Commission}
 - **Labor Regulations:** {Department of Labor}, {national labor relations board, nlr}, {union rights, card check, right to work, closed shop}, {wages and hours, overtime requirements}, {minimum wage, living wage}, {workers' compensation}, {Occupational Safety and Health Administration, osha, Mine Safety and Health Administration}, {employment at will, advance notice requirement, at-will employment}, {affirmative action, equal employment opportunity, eeoc}, {trade adjustment assistance}, {Davis-Bacon}, {ERISA}, {Pension Benefit Guaranty Corporation, PBGC}
 - **Immigration:** {immigration policy, immigration reform, migration reform}, {Immigration and Customs Enforcement, immigration and naturalization service}, {immigrant workers, immigrant labor}, {farm worker jobs program, farm worker program, farm worker program, farmworker program, guest worker program, guestworker program, H-2A program, H-2B program}, {H-1B program, H-1B visa}, {refugee crisis}, {Schengen}
 - **Energy and Environmental Regulation:** {energy policy}, {energy tax, carbon tax}, {cap and trade}, {cap and tax}, {drilling restrictions}, {offshore drilling}, {pollution controls, environmental restrictions, clean air act, clean water act}, {environmental protection agency, epa}, {wetlands protection}, {Federal Energy Regulatory Commission, FERC}, {ethanol subsidy, ethanol tax credit, ethanol credit, ethanol tax rebate, ethanol mandate, biofuel tax credit, biofuel producer tax credit}, {corporate average fuel economy, CAFE standard}, {endangered species}, {Keystone pipeline}, {Alaska oil pipeline, Trans-Alaska pipeline}, {greenhouse gas regulation, climate change regulation}, {Nuclear Regulatory Commission}, {Pipeline and Hazardous Materials Safety Administration}

- **Lawsuit and Tort Reform, Supreme Court Decisions:** {tort reform}, {class action reform}, {punitive damages reform}, {medical malpractice reform}, {lawsuit reform}, {Supreme Court}
- **Housing and Land Management:** {Federal Housing Administration}, {Federal Housing Finance Agency}, {Department of Housing and Urban Development, HUD}, {Section 8 Housing}, {Office of Fair Housing and Equal Opportunity, FHEO}, {Bureau of Land Management}, {Department of Interior}, {zoning regulations, zoning laws}, {endangered species}, {US Forest Service, United States Forest Service}
- **Other Regulation:** {Consumer Product Safety Commission}, {Department of Education}, {Small Business Administration}, {Federal Communications Commission, FCC}, {Fish and Wildlife Service}
- **National Security:** {national security}, {war, military conflict, military action}, {terrorism, terror, 9/11}, {defense spending, defense policy, military spending}, {Department of Defense}, {Department of Homeland Security}, {Defense Advanced Research Projects Agency, DARPA}, {armed forces}, {base closure}, {military procurement}, {no-fly zone}, {Syrian war}, {Iraq war}, {Libyan war}, {Ukraine conflict, Ukraine invasion, Crimean invasion, Crimean annexation}, {South China Sea conflict}, {naval blockade, military embargo}
- **Trade Policy:** {trade policy}, {tariff, import duty}, {import barrier, import restriction}, {trade quota}, {dumping}, {export tax, export duty}, {trade treaty, trade agreement, trade act}, {wto, world trade organization, Doha round, Uruguay round, gatt}, {export restriction}, {investment restriction}, {Nafta, North American Free Trade Agreement}, {Trans-Pacific Partnership, TransPacific Partnership}, {Federal Maritime Commission}, {International Trade Commission}, {Jones Act}, {trade adjustment assistance}
- **Healthcare Policy:** {healthcare policy}, {health insurance}, {Medicaid}, {Medicare}, {Affordable care act, Obamacare}, {malpractice tort reform, malpractice reform}, {VA hospital, VA healthcare, Veterans Affairs hospital, Veterans Affairs healthcare, Veterans Health Administration}, {National Institutes of Health}
- **Food and Drug Policy:** {prescription drug act}, {drug policy}, {food and drug administration, fda}
- **Transportation, Infrastructure and Public Utilities:** {Department of Transportation}, {Federal Highway Administration}, {federal highway fund}, {National Highway Traffic Safety Administration}, {U.S. Surface Transportation Board}, {Amtrak, National Railroad Passenger Corporation}, {Bonneville Power Administration, Tennessee Valley Authority, Southeastern Power Administration, New York Public Power Authority, Santee Cooper, South Carolina Public Service Authority, Salt River Project, Los Angeles Department of Water and Power}, {Corps of Engineers}, {Federal Aviation Administration, FAA}, {Federal Maritime Commission}, {National Aeronautics and Space Administration, NASA}, {Pipeline and Hazardous Materials Safety Administration}
- **Elections and Political Governance:** {presidential election}, {Congressional election}, {parliamentary election}, {presidential impeachment}, {Brexit}, {Scottish referendum}, {Grexit, Greek exit}, {Eurozone exit, Eurozone breakup}, {military takeover, coup}, {civil war}
- **Agricultural Policy:** {Department of Agriculture, USDA}, {ethanol subsidy, ethanol tax credit, ethanol credit, ethanol tax rebate, ethanol mandate, biofuel tax credit, biofuel producer tax credit}

Appendix C. Additional Analysis and Results

Figures C.1 and C.2 display the time series of residuals for the regressions reported in Table 2, Columns (1) and (3), respectively.

Table C.1 expands on the VIX regressions in Table 2 by using NVIX as an explanatory variable instead of, or in addition to, our EMV tracker. There are two main results in Table C.1: First, columns (1) to (4) show that EMV outperforms NVIX in tracking the VIX. Second, columns (5) and (6) show that EMV and NVIX have independent explanatory power in the sense that neither knocks out the statistical significance of the other. Moreover, including both explanatory variables substantially improves the goodness of fit.

Table C.1: Regressions of VIX on EMV and NVIX, January 1985 to March 2016

	(1)	(2)	(3)	(4)	(5)	(6)
EMV _t	0.75 (0.06)		0.43 (0.07)		0.55 (0.07)	0.36 (0.06)
NVIX _t		1.12 (0.12)		0.53 (0.11)	0.61 (0.12)	0.32 (0.07)
VIX _{t-1}			0.58 (0.08)	0.65 (0.05)		0.50 (0.07)
R ²	0.61	0.48	0.83	0.77	0.71	0.85
Observations	374	374	372	372	374	372

Notes: Each column reports a regression of VIX on the indicated row variables, using monthly data from January 1985 to March 2016. VIX is the monthly average of daily closing values on the CBOE 30-day implied volatility index from January 1990 onwards, appended to data from Berger et al. (2019) in earlier years EMV is Equity Market Volatility tracker developed in Section 2.1. NVIX is the news-based volatility measure developed in Manela and Moreira (2017) using front-page abstracts and headlines in the *Wall Street Journal*.

Table C.2 explores the sensitivity to alternative newspaper weightings in regressions of VIX on EMV. Column (1) replicates our baseline specification reported in Column (1) of Table 2. The remaining rows adopt the same regression specification but double the weight on each newspaper, one at a time, in constructing the EMV tracker (Panel A), drop each newspaper one at a time (Panel B), or use a single newspaper in constructing EMV (Panel C).

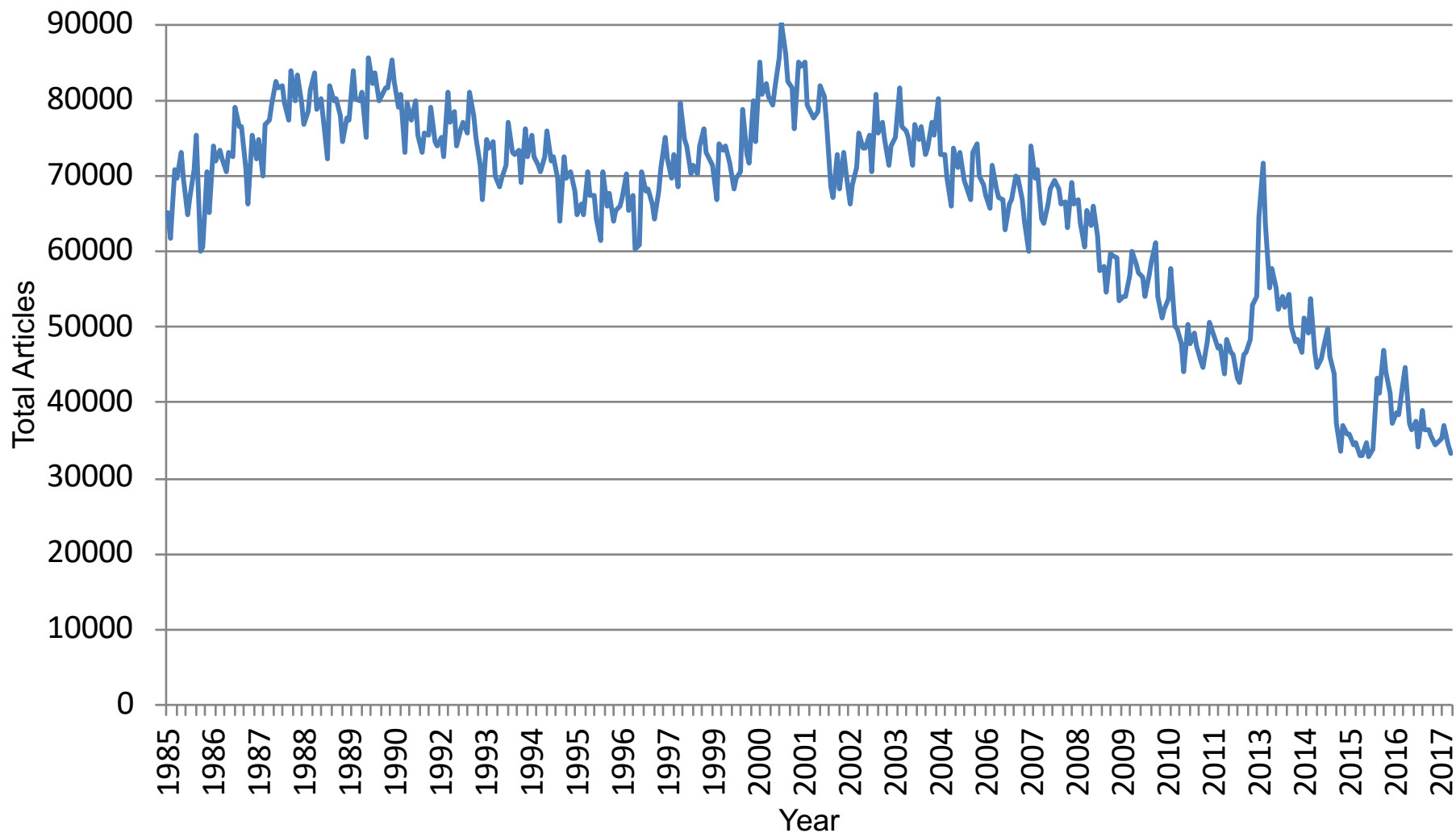
Figures C.3. displays a time series for the fraction of EMV articles that contain one or more of the “Policy” terms that Baker, Bloom and Davis (2016) use in constructing their newspaper-based Economic Policy Uncertainty Index for the United States. Figures C.4 to C.7 display additional category-specific EMV trackers.

Table C.2: Fit Sensitivity to Alternative Newspaper Weightings in Regressions of VIX on EMV, 1985-2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Dallas MN	Houston Chronicle	Miami Herald	SF Chronicle	USA Today	Boston Globe	Chicago Tribune	WSJ	NYT	LAT	Wash. Post
Panel A: Doubling the weight on the indicated newspaper												
EMV _t	0.76 (0.06)	0.76 (0.06)	0.74 (0.06)	0.75 (0.06)	0.74 (0.06)	0.75 (0.06)	0.75 (0.06)	0.77 (0.06)	0.78 (0.06)	0.78 (0.06)	0.75 (0.06)	0.76 (0.06)
R ²	0.611	0.607	0.604	0.615	0.611	0.606	0.609	0.604	0.613	0.607	0.600	0.608
Panel B: Dropping the indicated newspaper												
EMV _t	0.76 (0.06)	0.75 (0.06)	0.78 (0.06)	0.76 (0.06)	0.77 (0.06)	0.76 (0.06)	0.76 (0.06)	0.74 (0.06)	0.73 (0.06)	0.72 (0.06)	0.77 (0.06)	0.76 (0.06)
R ²	0.611	0.603	0.613	0.598	0.603	0.607	0.605	0.611	0.598	0.603	0.618	0.610
Obs.	396	396	396	396	396	396	396	396	396	396	396	396
Panel C: Using only the indicated newspaper												
EMV _t	0.76 (0.06)	0.29 (0.04)	0.39 (0.05)	0.39 (0.05)	0.35 (0.04)	0.36 (0.05)	0.40 (0.05)	0.53 (0.04)	0.52 (0.09)	0.45 (0.09)	0.45 (0.06)	0.59 (0.06)
R ²	0.611	0.226	0.393	0.406	0.378	0.329	0.349	0.344	0.346	0.237	0.353	0.468
Obs.	396	396	396	396	396	396	396	396	396	396	396	396

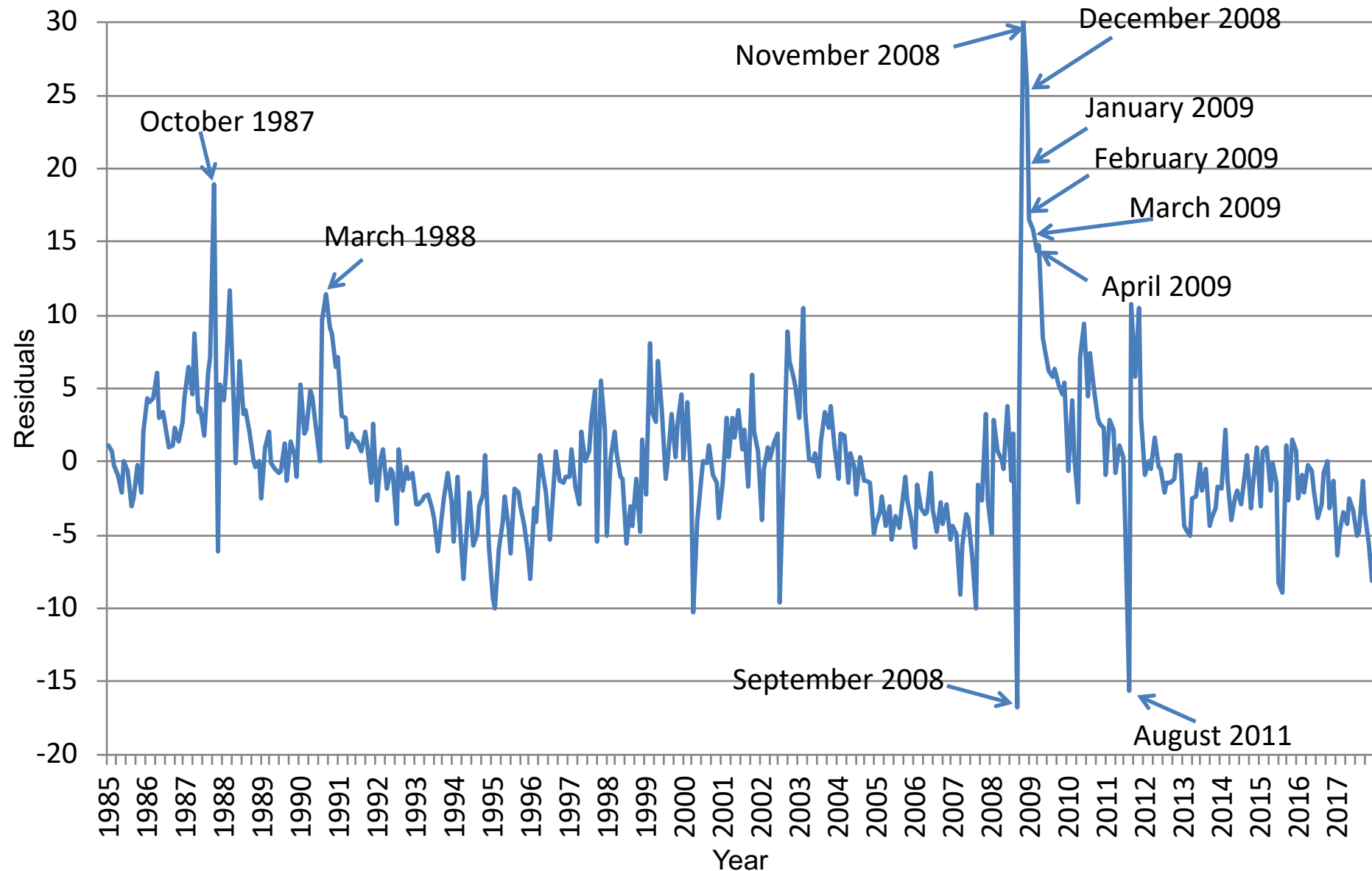
Notes: All series are at the monthly level. EMV is the Equity Markets Volatility Index. The dependent variable is always the VIX where VIX refers to the monthly average of daily close of the VIX implied volatility index on the S&P500. Columns (2)-(12) of Panel A correspond to a different version of our EMV Index as the independent variable where the version is constructed such that the column title newspaper has twice the weight as the other newspapers. Columns (2)-(12) of Panel B correspond to a different version of our EMV Index as the independent variable where the version is constructed such that the column title newspaper has been removed from the index. Robust standard errors in parentheses. The slope coefficient is statistically significant at the 1% level in all regressions.

Figure A.1: Total Number of Newspaper Articles, Monthly, 1985-2017



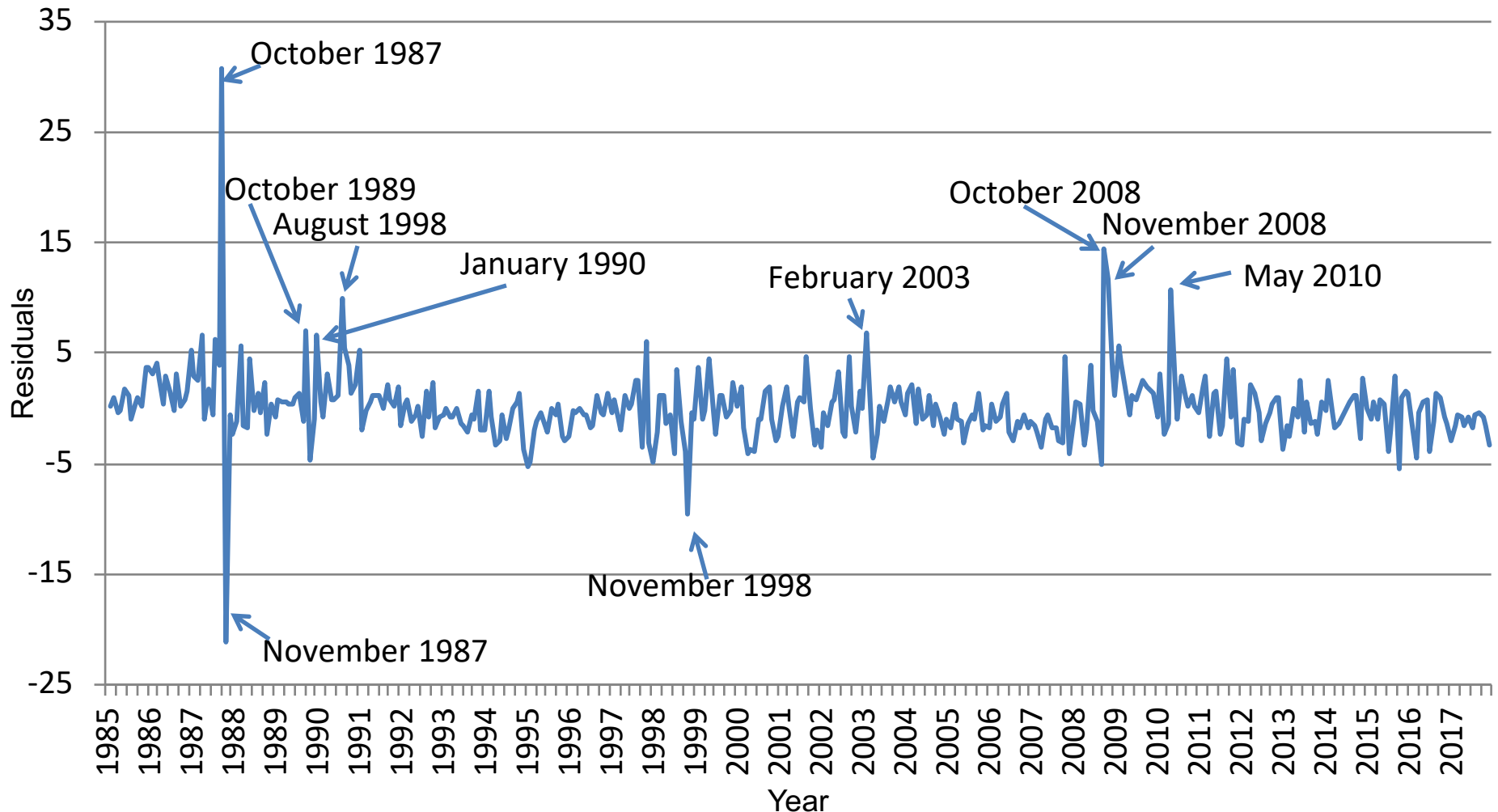
Notes: This chart shows the total number of articles in the eleven newspapers that enter into our EMV tracker. As discussed in Appendix A, digital archives for certain of our newspapers are unavailable near the beginning or end of our sample period. We scale up the article counts for non-missing papers to adjust for missing papers in certain periods.

Figure C.1: Residuals in Regression of VIX on EMV, 1985-2017



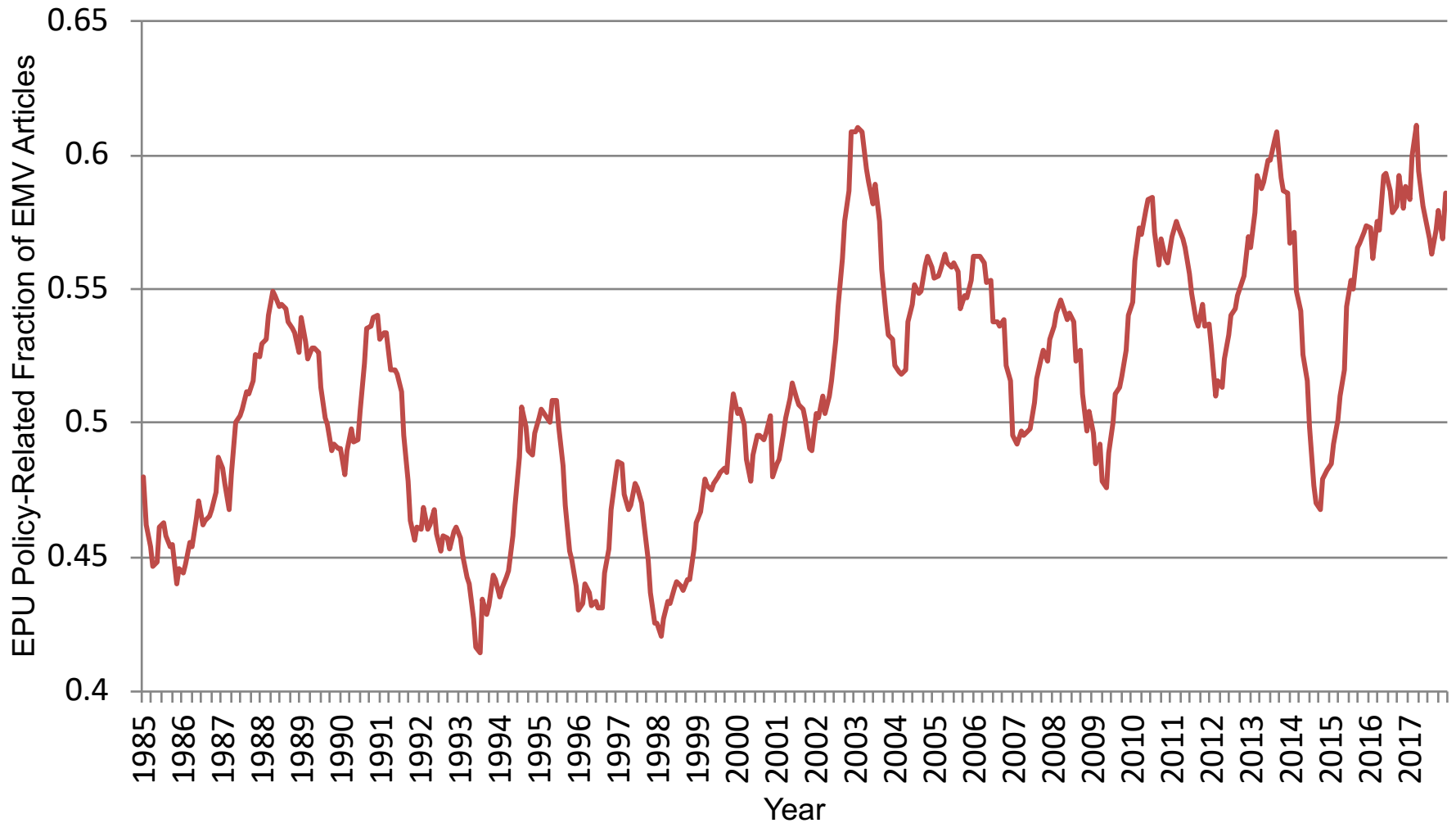
Notes: The residuals are for the specification in Column (1) of Table 2 and run from January 1985 to December 2017.

Figure C.2: Residuals in Regression of VIX on EMV and Lagged VIX, 1985 to 2017



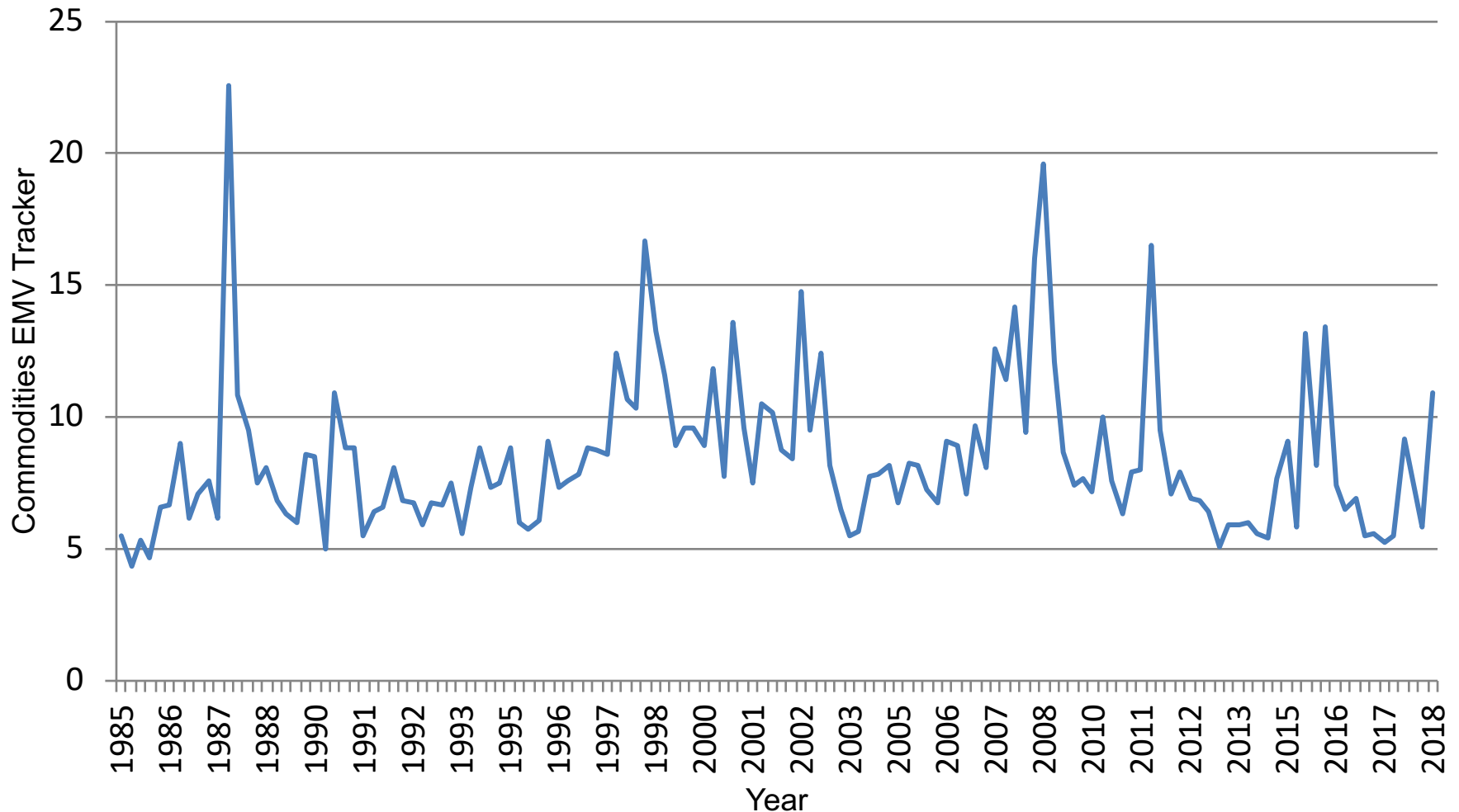
Notes: The residuals are for the specification in Column (3) of Table 2 and run from January 1985 to December 2017.

Figure C.3: Fraction of EMV Articles that Contain an EPU Policy Term, 1985-2017, 12-Month Moving Average



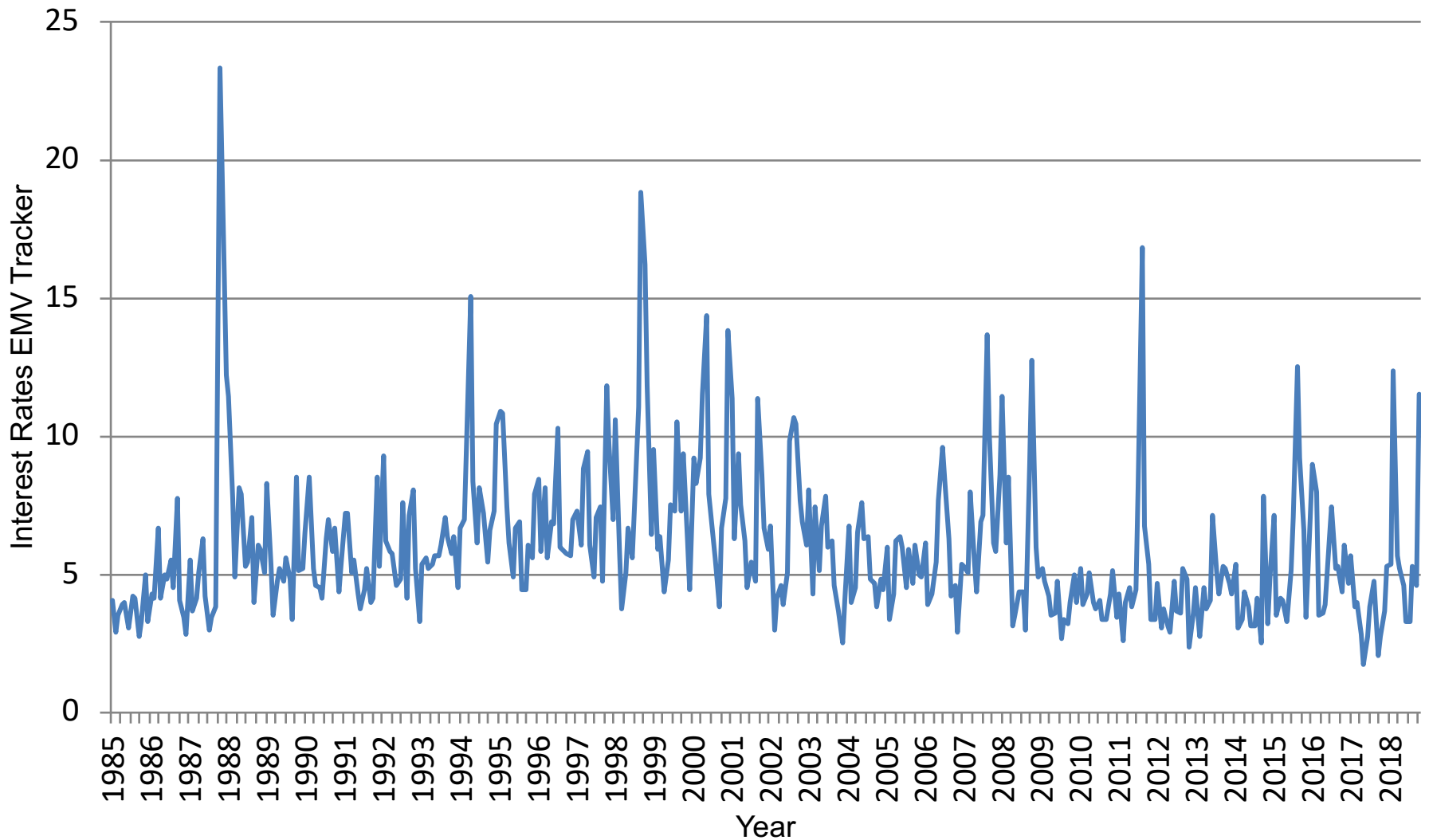
Notes: This chart shows the fraction of EMV articles that contain one or more of the policy terms used to construct the U.S. EPU Index of Baker, Bloom and Davis (2016). We compute this fraction for each newspaper and month, average over papers by month, and then compute a moving average with six lags and leads, truncating lags (leads) near the sample start (end).

Figure C.4: Commodity Markets EMV Tracker, 1985 to 2018



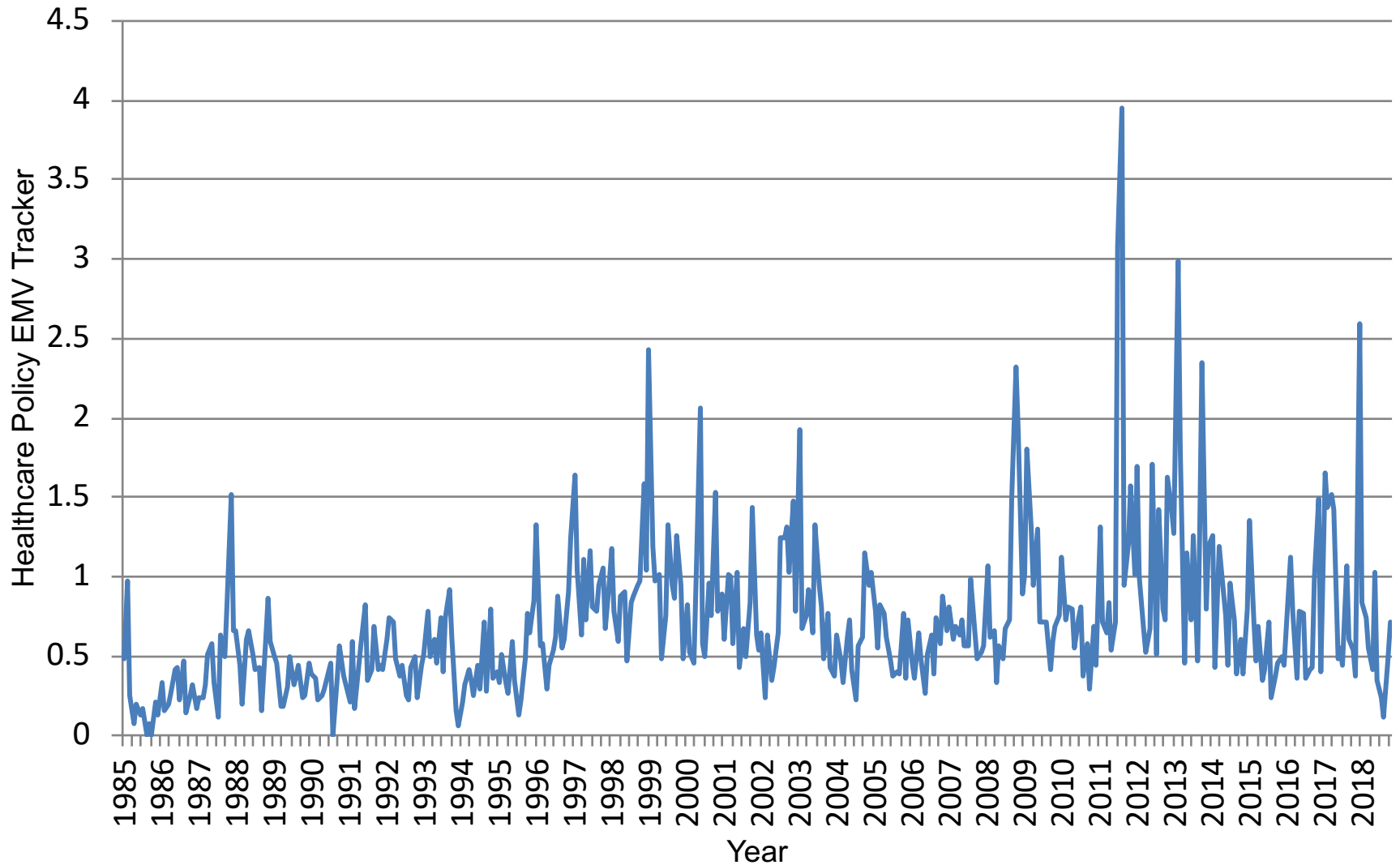
Notes: We construct the Commodity Markets EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Commodity Markets**. See Appendix B for the list of terms.

Figure C.5: Interest Rates EMV Tracker, 1985-2018



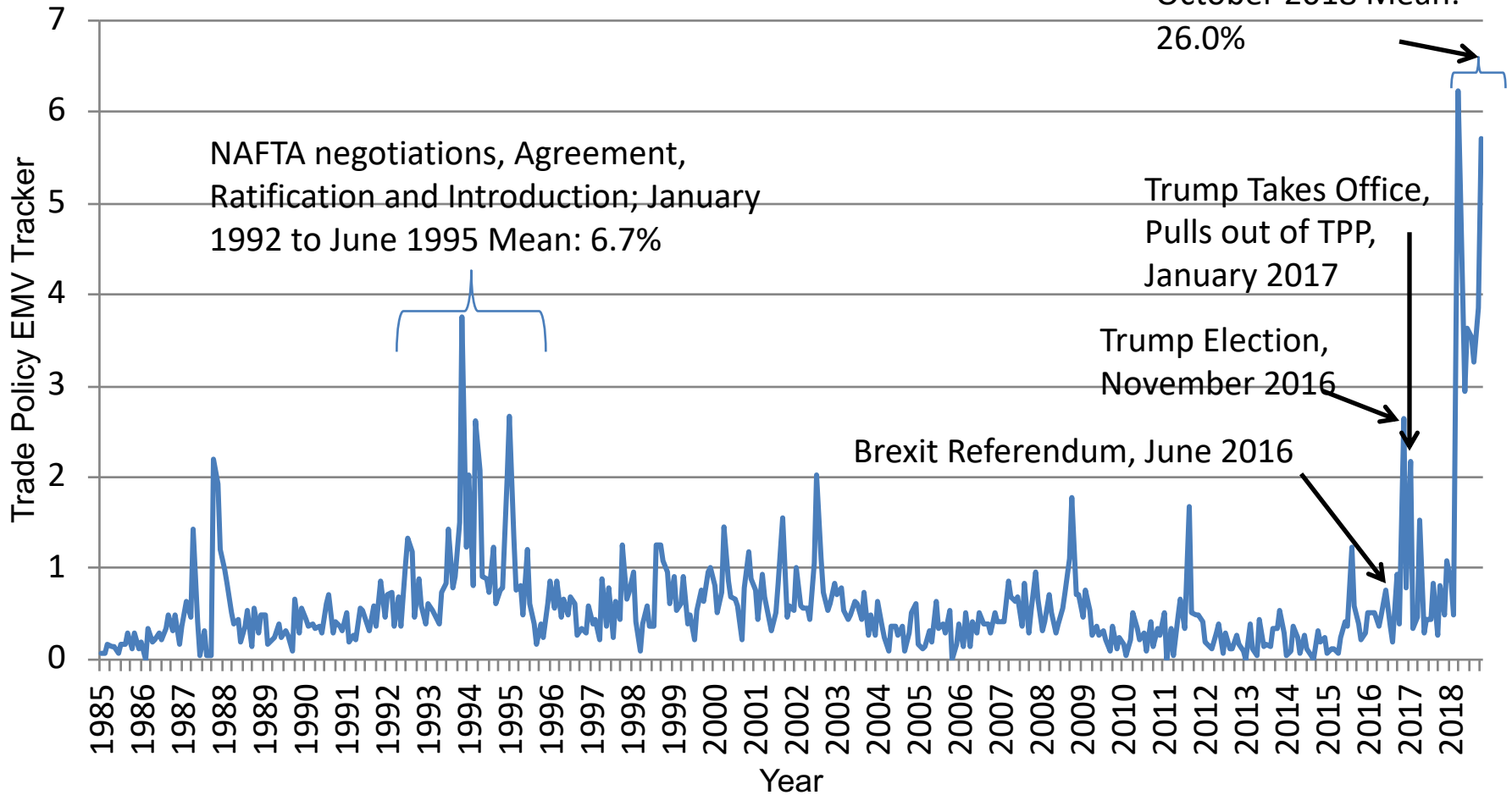
Notes: We construct the Interest Rates EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Interest Rates**. See Appendix B for the list of terms. 50

Figure C.6: Healthcare Policy EMV Tracker, 1985-2018



Notes: We construct the Healthcare Policy EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Healthcare Policy**. See Appendix B for the list of terms.

Figure C.7: Trade Policy EMV Tracker, 1985-2018



Notes: We construct the Trade Policy EMV tracker as the product of our overall EMV tracker and the share of EMV Articles that contain one or more terms in **Trade Policy**. See Appendix B for the list of terms.