Discussion Papers in Economics

No. 02/2021

The High Frequency Impact of Economic Policy Narratives on Stock Market Uncertainty

Daniel Perico Ortiz
FAU Erlangen-Nürnberg

ISSN 1867-6707

Friedrich-Alexander-Universität Erlangen-Nürnberg
Institute for Economics
https://www.iwf.rw.fau.de/discussion-papers/

The High Frequency Impact of Economic Policy Narratives on Stock Market Uncertainty

Daniel Perico Ortiz*†

Friedrich-Alexander-Universität Erlangen-Nürnberg

February 22, 2021

Abstract

This paper investigates the causal relationship between economic policy narratives, derived from President Trump's tweets and tweeting behavior, and stock market uncertainty. To this end, I define different event types based on the occurrence probability of identified narratives or unusual tweet behaviors. High-frequency market uncertainty responses to different events are recovered using time-series regressions. Events regarding foreign policy, trade, monetary policy, and immigration policy exhibit a significant effect on market uncertainty. Impulse responses become significant between one and three hours after the event occurs, for most of the events. Furthermore, behavior events, such as increases in the tweet or retweeted counts above their average, matter for stock market uncertainty.

Keywords: Twitter, Donald Trump, Economic Narratives, Economic Policy Uncertainty, VIX.
JEL classification: D83, E71, C54.

1 Introduction

Social networks have rapidly gained relevance as a source of information for economic agents when forming expectations about future events, especially at short time horizons. Recent research on sentiment analysis based on Twitter data, such as Piñeiro-Chousa et al. (2016), Yang et al. (2015), and Schnaubelt et al. (2020), suggest that the continuous flow of information through social media may cause movements in market indicators and asset prices. Economic and financial media coverage of President Trump's social media behavior reflects the public concerns regarding the adverse effects of misuse of official social media channels, particularly when used to disclose information regarding future economic policies[1]. This case provides an opportunity to understand the increasing role of social networks in economic phenomena, such as stock market uncertainty.

An economic narrative approach appears suitable to investigate the effect of Trump's twitting behavior on perceived uncertainty in financial markets since a collection of presidential tweets regarding a specific topic fits the definition of a narrative. According to Shiller (2017), a narrative is a composite of facts and emotions that form an impression on the human mind. It expresses an explanation of events that people want to bring up in conversations, on the news, or on social networks, since it stimulates the concerns and emotions of others. Its form varies through time and across tellings, but its core is successful in spreading. Trump's tweets are simple by default due to the constrain in the number of characters per tweet. Trump's tweets intend to reach a broad audience. Contrary to official statements and releases, Trump-tweet's implied narratives are a mixture of facts and emotions. He writes tweets in such a way that they appeal emotionally to his readers. At the same time, they convey different types of facts, ranging from official statistics and staff changes to "alternative facts"[2]. Finally, Trump's tweets have the potential to spread virally among supporters and detractors. This paper deals with economic narratives[3] exclusively since one can interpret them as causative innovations to fluctuations in the aggregate economy, Shiller (2017).

*Corresponding author: Lange Gasse 20, 90403 Nürnberg, Germany. daniel.perico@fau.de.

†I thank Prof. Dr. Jonas Dovern, and the colleagues at the Statistics and Econometrics Department at the Friedrich-Alexander-Universität Erlangen-Nürnberg for their valuable comments.

[1]Bloomberg even created a website dedicated to tracking on real-time Trump tweets relevant to financial markets. See www.bloomberg.com/features/trump-daily.

[2]One example is the size of the crowd attending to president Trump's inaugural ceremony. See @trumpalterfacts for a collection of President Trump's alternative facts.

[3]For recent examples of literature employing a similar approach in financial markets see Hanna et al. (2020), in public policy and inequality see Shiller (2019b), in monetary economics see Larsen et al. (2020), in cryptocurrencies see McBeth et al. (2018), and in financial crises see Azqueta-Gavaldón (2020), and Shiller (2020).

The goal of this paper is to test the hypothesis of whether or not Trump's tweet behavior and tweet based economic policy narratives are causative innovations to perceived stock market uncertainty. Therefore, this study addresses two main questions: First, does Trump's tweet behavior, measured in tweet and retweet frequency, with its consequent reaction in terms of retweeted and favorite counts, cause fluctuations in market uncertainty perceptions? Second, do narratives regarding economic policy cause fluctuations in market uncertainty perceptions? To test this, I use a three-step methodology. First, I use unsupervised machine learning to identify the main topics from the tweet sample and cluster them based on their linguistic distance. I generate meta-topics by aggregating topics at the cluster level and label each meta-topic according to its implied narrative. Second, I use the estimated topic and meta-topics probabilities as intermediate inputs for the generation of event variables. In this step, I also generate events based on tweet activity rather than on tweet content. Third, I estimate the effect of selected events on the change in the VIX index, as a proxy for market uncertainty at the high-frequency level, employing time-series regressions and local projections over an estimation window covering from 15 minutes before the event up to five hours afterward.

This paper contributes to the literature on economic policy uncertainty by providing evidence for high-frequency market uncertainty effects of policy narratives contained in informal policy announcements delivered through social media. Meta-topic events for foreign policy, trade, and immigration have a statistically significant uncertainty promoting effect. Monetary policy narratives, with high levels of retweeting, show the highest estimated impact on market volatility. The timing of the effect is also relevant. Responses are significant and achieve their peaks between 1.5 and 4.5 hours after the event, except immigration, which attains its maximum at the end of the estimation window. Events regarding unexpected changes in Trump tweet behavior, especially when tweets[4] (excluding retweets) and retweeted counts are above their average (high activity periods), have a statistically significant positive impact on market volatility. A separate analysis using the change in the EPU index as uncertainty measure at the daily frequency provides additional evidence of significant effects of economic policy narratives at a lower frequency levels.

This paper falls at the intersection of two strands of literature. The first strand deals with the impact of news and announcements on financial markets. Authors providing evidence on the sensitivity of asset prices to the disclosure of unexpected macroeconomic indicators and FOMC statements include Beechey et al. (2009), for nominal and Treasury Inflation-Protected Securities (TIPS), and Lapp et al. (2012) for federal funds rate futures prices. More recently, Gilbert et al. (2017) shows that the heterogeneity in asset price responses depends on the intrinsic value of the announcement, which relates to its forecasting power.

Other authors explore the impact of macroeconomic announcements on stock market volatility. Graham et al. (2003) shows that announcements regarding employment, NAPM (manufacturing), producer price index, import and export price indices, and employment cost index have a significant impact on stock valuation defined in terms of implied volatility. In the same line, Clements (2007) suggests that the VIX index falls significantly on the day of FOMC meetings. Investigations of Bomfim (2003) and Lee et al. (2019) reaffirm the importance of the timing of the announcements for volatility dynamics. Clements (2007) links pre-announce periods to relatively calm levels of conditional volatility. Finally, Lee et al. (2019) suggests that the effect of announcements, especially monetary policy ones, are also more pronounced in the crisis and post-crisis periods than in the pre-crisis period.

The second strand of literature related to his paper deals with political and policy uncertainty events and market outcomes[5]. Studies from Baker et al. (2016), Bittlingmayer (1998), and Voth (2002) find a positive relationship between political uncertainty and stock market volatility. Belo et al. (2013) links the cross-section of stock returns to firms' exposures to the government sector. The positive relation between policy uncertainty and options volatility is documented in Pástor et al. (2013), Kelly et al. (2016) and Amengual et al. (2018) for monetary policy uncertainty.

Within this category falls the literature regarding Trump's tweeting behavior. Colonescu (2018) studies the effect of tweets on foreign exchange markets. Bianchi et al. (2019) provides evidence on the impact of tweets on Fed funds futures. Kinyua et al. (2021) documents the intra-day response of the S&P 500 and DJIA indexes to Trump's tweets using sentiment analysis. Baker et al. (2019), and Fendel et al. (2020) demonstrate the connection between Trump announces regarding trade policy and an increase in stock market volatility. Burggraf et al. (2020) provide evidence on the direction of the causal relationship between Trump tweets to returns and the VIX. Klaus et al. (2020) show a similar effect for European financial markets. Finally,

[4]Tweet refers to self-written posts. Note the difference between a retweet and retweeted. The first relates to posts Trump shares from other accounts or his own; the second refers to the number of times someone shares one of his tweets or retweets. Total count is the sum of tweets and retweets.

[5]This paper also fits the literature on the effect of political events, such as elections. However, the focus of this paper is on economic and policy events. For literature related to elections, uncertainty, and high abnormal stock returns see Pantzalis et al. (2000) and Bialkowski et al. (2008) for evidence from national elections in different countries, and Li et al. (2006) for U.S. presidential elections. For studies featuring changes in option-implied volatility around elections see Gemmill (1992) and Goodell et al. (2013).

Fan et al. (2020) studies firm-level exposure around political events by using a (dis)agreement among social media users who jointly mention firms from the S&P 500 composite and Trump.

This paper is structured as follows. Section 2 describes the data. Section 3 presents the three-step methodology to estimate the effect of tweet based events on uncertainty measures. Section 4 presents results on the high-frequency effects of identified narrative and behavior events on stock market uncertainty, given by the change in the VIX. Section 5 concludes.

2 Data

I use three data sources for the empirical analysis, namely Donald Trump's tweets, the closing prices of the CBOE 3-Month Volatility Index (VIX3M) at five-minute frequency, and the daily U.S. EPU index. The tweets sample covers the period between December 31, 2015, to October 21, 2019. I retrieved Twitter data from the account @realdonaldtrump using the Twitter API, and from trumptwitterarchive.com. Each observation or post[6] in this sample is either a tweet or retweet text, accompanied by metadata such as timestamp[7], an indicator of whether the text is a tweet or a retweet, the number of times it was retweeted, and the number of times it was marked as a favorite. The VIX and EPU data samples span over the same period as the twitter sample.

Table 1: Summary statistics for Twitter data

	Day sample				Five-minutes sample			
	Mean	S.d.	Min	Max	Mean	S.d.	Min	Max
	Panel A: Tweet variables before merge with uncertainty series							
Posts	11.81	9.58	1	87	1.25	0.82	1	16
Tweet	9.57	6.51	0	87	1.018	0.53	0	7
Retweet	2.23	5.52	0	65	0.237	0.86	0	16
Favorite	71,897	58,280	0	879,647	61,004	51,310	0	879,647
Retweeted	18,500	14,466	37	369,530	16,584	12,943	0	369,530
Obs.				1404				13210
	Panel B: Tweet variables after merge with uncertainty series							
Posts	10.9	9.50	0	87	0.010	0.152	0	15
Tweet	8.86	6.60	0	87	0.008	0.104	0	5
Retweet	2.03	5.24	0	65	0.002	0.103	0	14
Favorite	67,479	58,570	0	879,647	404.6	6,257.5	0	330,560
Retweeted	17,228	14,493	0	369,530	113.5	1,638.7	0	168,765
Obs.				1,413				241,666

Note: This table presents summary statistics for the tweet sample retrieved from the account @realdonaldtrump via twitter API and trumptwitterarchive.com. The sample period ranges between 31.12.2015 23:11 CST to 21.10.2019 12:31 CST. Note that favorite count for retweets is always zero. Uncertainty series for the day sample is the daily value of the US EPU index, for the five-minute sample is the close value of the VIX at the same frequency. Uncertainty measures are used as base for the merging process given the larger data availability.

I transform the original tweet sample into two different data samples by concatenating posts texts within a five-minute or a day interval and aggregating post metadata at the same level. The resulting five-minute and day tweet samples are then merged with the respective uncertainty series (VIX for the five-minute sample and EPU for the day sample) to generate the consolidated data samples. After the merge process, I set tweet variables to zero for periods without tweet activity and discard observations with tweet activity but missing uncertainty measure data.

Table 1 presents summary statistics for the Twitter samples and provides insights into Trump's tweet behavior. Panel A in table 1 shows that he publishes on average 12 posts (tweets or retweets) per day, and more than one post per five-minute interval on average. A breakdown analysis of the total post counts shows that he prefers to tweet himself, almost ten tweets per day, as opposed to retweet external content. The maximum observed tweet count is seven tweets in less than five minutes and 87 tweets per day. Favorite and retweeted counts report followers' behavior in terms of how many times a post is liked and how many times it is shared. These two variables are observed ex-post, i.e. their values represent their counts when the data is downloaded from the API and not during the day or five-minute interval. Summary statistics for favorite and retweeted count do not change much in the upper panel of Table 1, indicating that it is a single post or a series of posts within five minutes that drives the daily followers' behavior. Finally, variables do not change much after the merge process in the day sample since there are only nine days in which there is uncertainty

[6]Hereafter I will use the word *post* to refer to an observation independent if it is a *tweet* or *retweet*. In a time interval, *posts* will refer to the sum of tweets and/or retweets counts within the interval. I will use the term *total count* and *posts* interchangeable.

[7]Timestamps come originally in UTC. I transform them to CST time to match the VIX data sample.

data but no tweet activity. In the five-minute case, after the merge $228,456$ periods without tweet activity periods are added.

3 Methodology

The narrative approach in this paper consists of a three steps methodology. Section 3.1 describes how the main topics from each of the tweet samples are estimated and then clustered into meta-topics regarding different narratives. Section3.2 uses the estimated probabilities of topics and meta-topics as an intermediate input for the generation of event variables. Section 3.3 describes the regression model used to estimate the effect of selected events on different uncertainty measures.

3.1 Topic modelling

This section introduces the topic modeling approach, one could think of a fictive Trump follower who is aware of Trump's characteristic writing style and reads all posts available. This follower derives the main narrative behind each tweet, relates this story to similar ones, and groups them into K categories or topics. Finally, he or she reports how Trump allocates his attention among these categories for each period[8]. To accomplish this, I rely on an unsupervised learning algorithm based on the Latent Dirichlet Allocation (LDA) model, described in Blei et al. (2003). I define two LDA models based on two different corpora, one for the five-minute sample and one for the day sample. Each corpus is composed of a set of documents D, $d = (d_1, \ldots, d_D)$, which are the concatenation of tweet or retweet texts within the time interval. Each document is composed of a number terms from a vocabulary of size V, with unique and pre-processed terms[9] w_i for all $i = 1, \ldots, V$. Table 2 presents summary statistics for these text corpora and provides additional insight into Trump's tweeting behavior. The difference in the average vocabulary size between both corpora is only slightly more than three terms, even though the common document size of the day corpus is nine times larger. This indicates that Trump's topics do not vary much within a day or handle very few, therefore one can expect similar estimated topics from the LDA algorithm at both frequencies.

Table 2: Summary statistics for text corpora

	Day			Five-minutes		
	count	mean	s.d.	count	mean	s.d.
Documents	1,404	11.81		13,210	1.25	
Vocabulary size	25,007	25.3	15.93	25,007	22	18.79

Note: This table presents summary statistics for corpora based on tweets and retweets text retrieved from @realdonaldtrump via twitter API and trumptwitterarchive.com. The sample period is from 31.12.2015 23:11 CST to 21.10.2019 12:31 CST.

The LDA algorithm interprets each document in the corpus as a mixture of estimated topic terms based on the underlying topic probabilities, θ_K. One advantage of this type of model is that it requires little parametrization beyond the number of topics, K. Inference about topic probabilities is drawn from the Gibbs sampling algorithm as in Griffiths et al. (2004) and implemented in R as in Hornik et al. (2011). I define the optimal number of topics for each LDA specification based on maximum mean and median coherence in the region where perplexity is strictly below the average over all possible specifications. This approach suggests 50 topics as the optimal number for the five-minute LDA model, K^*_{5-min}, and 40 for the day model, K^*_{day}. The estimated topics from these specifications are sets of top-terms (decreasing order) describing each of them.

Further, I hierarchically cluster these topics based on their linguistic distance, given by the Hellinger distance, Hd, between estimated topic probabilities, $\hat{\theta}_k$. I define similar topics within a cluster as meta-topics, m_i for $i = 1, \ldots, M$, and label them according to its implied narrative[10]. For example, topics $k =$ 36, 7, and 16 belong to the same cluster. These three topics share some trade and foreign policy keywords within their top-terms, but they imply different individual narratives, such as trade war with China, talks with North Korea, or trade with Mexico. These individual stories converge to a broader narrative of the

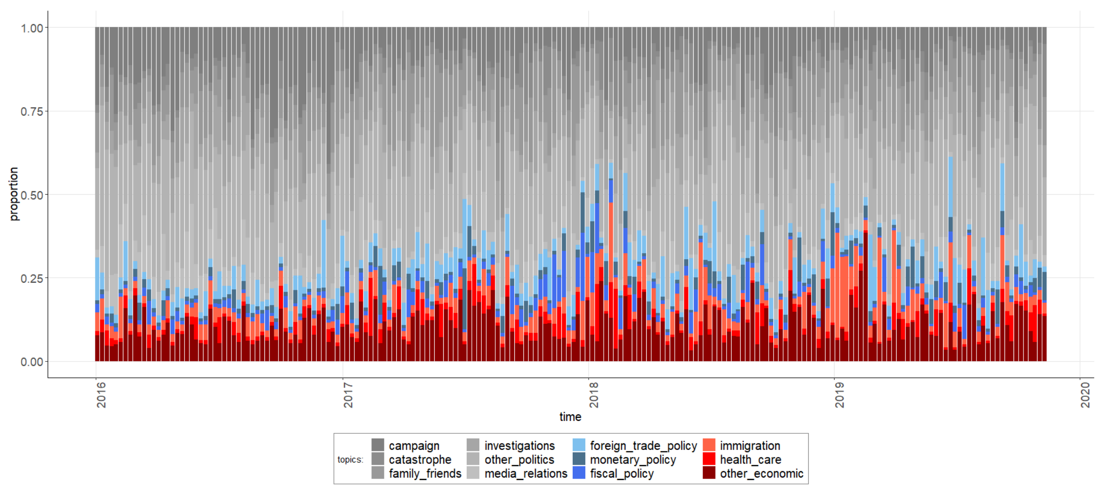
[8]Bybee et al. (2020) uses a similar approach to extract topics from a corpus-based on news from The Wall Street Journal. They interpret the posterior distribution of topics over documents $\hat{\theta}_K$ as the proportion of attention given by the journal to a specific topic at a specific point in time.

[9]See appendix A.1 for further details on text pre-processing.

[10]Meta-topics are defined by the largest cluster below a distance threshold, set here to $Hd = 0.7$ for the five-minute sample, and $Hd = 0.4$ for the day sample. Originally 15 meta-topics were identified for the five-minute sample. I merge some politics meta-topics for simplification (for example, "campaign 1" and "campaign 2") without compromising the composition of economic meta-topics. See Figure A.2 and A.3 for the distribution of topics by cluster.

type *"President Trump's approach to foreign trade and foreign policy issues"*[11], identified in meta-topic m_7. Figure 1 plots the distribution of the 12 identified meta-topics, at weekly aggregation, over time. Appendix A presents a more formal description of the topic modeling, including further definitions, results for the optimal number of topics, and the top 10 words for the definitive LDA models.

Figure 1: Meta-topics distribution over time, weekly aggregation



Note: Average probability of a meta-topic over a seven-day period. The probability of a meta-topic is the sum of the probabilities of its constituents. Meta-topics in gray tones refer to politic narratives.

Figure 1 summarizes the main results for this section. In this figure, one can identify 12 meta-topics from the five-minute sample. The first six meta-topics appear in gray tones and refer to political affairs, while the remaining six relate to economic-related policy affairs. On average, around three-quarters of the meta-topics proportions per week relates to political issues and only one quarter to economic and policy issues. This figure is also a good indicator of the accuracy of the LDA model, given that the distribution of topic overtime match the timing of the main events of Trump's presidency, such as the presidential campaign and debates in 2016, the hurricane in 2017, the tax cut and jobs act 2017/2018, the 2018/2019 trade wars, and the 2019 impeachment inquiry.

3.2 Events generation

In this section, I define event variables based on three criteria: *i*) different points in the distribution of the count variables, *ii*) the occurrence of topics, and *iii*) the occurrence of meta-topics. The intuition behind event creation is that an event occurs when President Trump generates a new post, and an existing narrative identifies it. The event triggers a transmission mechanism, which could be the retweeting channel, the news, or word-of-mouth, that allows the implied story to spread over the general public. In case the post is not identified with an existing narrative, then the event does not occur, and the spreading mechanism is not triggered.

The first type of events are events based on the distribution of count variables, or behavior events, since their implied narrative regards to unusual tweeting behavior of Trump himself or his followers, materialized in tweet count variables being above expected thresholds. Specialized and general media explicitly promote these types of narratives. One example of this is the media coverage of the Volfefe index created by JP Morgan[12]. Equation 1 describes how behavioral events are generated. The *count condition* in Equation 1 could take any form, such as *"more than two retweets in five minutes"* or *"retweeted count is above the sample mean"*. These types of events are independent of the tweet's content and are given by:

$$event_{b,t} = \begin{cases} 1 & \text{if count condition is true at period } t \\ 0 & \text{if count condition is false at period } t \end{cases} \tag{1}$$

The second type of events, single-topic events, are based on estimated topic probabilities. Equation 2 shows how single-topic events are generated. For each document and each topic, I create a set of dummy variables that are equal to one if a topic probability over documents, $\hat{\theta}_{k,t}$, exceeds a threshold set to 0.1, indicating that this topic is primary for a document, d, at period t, and zero otherwise[13]:

[11] Topic 10 is a constituent of the meta-topic event *foreign policy and trade* due to the close similarity with the top-terms of the other topics in this cluster. In fact, topic 10 fluctuates between *general economics* and *foreign policy and trade* clusters when rendering the dendrogram plot several times.

[12] Evidence for this claim can be obtained easily from a Google News search using the keyword Volfefe index. This index, and the news about it, basically states that President's Trump tweet behavior has a statistically significant impact on treasury yields.

[13] I set the threshold value based on the distribution of the maximum probability value per document.

$$event_{k,t} = \begin{cases} 1 & \text{if } \hat{\theta}_{k,t} > threshold, \qquad \forall k \in K \\ 0 & else \end{cases} \tag{2}$$

Analog to the topic events, I generate events for meta-topics as follows:

$$event_{m,t} = \begin{cases} 1 & \text{if } \sum_{k=1}^{m} \hat{\theta}_{k,t} > threshold, \qquad \forall k \in m \in M \\ 0 & else \end{cases} \tag{3}$$

The difference between a topic and meta-topic events relies on the trade-off between the level of specificity of the underlying narrative and the number of events satisfying the threshold condition. In this paper, I concentrate on events based on meta-topics for two reasons: First, presidential tweets seek to address the general public and spread widely, so that one can expect, and observe, ambiguous language in the tweets, such that similar keywords identify more than one topic. Second, inference about the effect of single-topic events rely on fewer observations leading to low variation in the predictor variables, and thus lower precision on the estimated responses. Table 3 provides a summary of the resulting meta-topic events at five-minute frequency, before and after the merge with the VIX series. In the five-minute sample, the number of events and their probability reduces drastically after the merge due to a high number of VIX observations without corresponding tweet activity.

Table 3: Meta-topics events summary for five-minute sample

Label	Coherence	Events		Probability	
		Before merge	After merge	Before merge	After merge
Campaign	0.0451	4,479	888	0.1674	0.0036
Catastrophe	0.0777	955	122	0.0398	0.0005
Family and friends	0.0356	2,302	405	0.0841	0.0016
Investigations	0.0397	5,356	1,326	0.2129	0.0054
Other politics	0.0304	2,397	443	0.0941	0.0018
Media relations	0.0598	2,320	391	0.0860	0.0016
Foreign policy and trade	0.0498	1,913	347	0.0782	0.0014
Monetary policy	0.0676	1,045	134	0.0414	0.0005
Fiscal policy	0.0265	993	158	0.0386	0.0006
Immigration	0.0733	949	137	0.0392	0.0005
Health care	0.0783	989	135	0.0393	0.0005
Other economic	0.0424	1,997	338	0.0784	0.0013

Note: This table presents a summary of meta-topic events based on tweets and retweets text retrieved from @realdonaldtrump via Twitter API and trumptwitterarchive.com. The sample period is 31.12.2015 23:11 CST to 21.10.2019 12:31 CST. The five-minutes Twitter sample is composed of 13210 observations. The five-minutes VIX sample is composed of 241666 observations. For a definition of the coherence measure, see appendix A.3. for a formal definition of the coherence measure.

3.3 Verification of event effects on uncertainty measures

To estimate the effect of meta-topic events or behavior, I follow an announcement approach as in Beechey et al. (2009) as well as Gilbert et al. (2017), using uncertainty measures as the dependent variable similar to Graham et al. (2003). In general, I estimate the following regression to examine the impact of the selected events on different uncertainty measures.

$$\Delta y_{t+h} = \alpha_h + \sum_{j=1}^{J} \beta_{j,h} event_{j,t} + \lambda x_t + \epsilon_{t+h}^{h}. \tag{4}$$

Therein, Δy_{t+h} is the change in the uncertainty measure index from l periods before the event to h periods afterward. I generate a set of variables denoted as Δvix_{t+h} for the change in the VIX (in percentage points, pp) in the window from l equal to 15 minutes to h equal to 60 periods or 5 hours. Similarly, I define a set of variables Δepu_{t+h} for the difference in the log value of the EPU index from l equal to one day to h equal to 30 days[14]. The time-invariant intercept is denoted by α. Standardized events of the type j enter in the regression as independent variables. This specification allows for multiple events (of the same or different type) to happen simultaneously. Controls in this regression take the form of raw counts in the vector x_t. Total count, tweet, and retweet counts never enter together in regression 4 to avoid multicollinearity. Favorite and retweeted counts are log-transformed and estimated independently of each other due to correlation issues. This regression runs over all windows where there is at least one event. Events and count variables are set to zero for periods when the total count is equal to zero. Coefficients from Equation 4 are obtained via ordinary least squares (OLS) with heteroskedasticity consistent (HC) standard errors.

[14] For summary statistics see table B.1 in the appendix.

Equation 4 implies a multi-step forecast that can be formulated in terms of Local Projections (LP), as proposed by Jordà (2005). Equation 5 shows the LP representation for an identified *shock event* at period t:

$$\Delta y_{t+h} = \alpha_h + \beta_h shock\ event_t + \sum_{i=1}^{I} \delta_{j,h} control\ events_{j,t} + \lambda x_t + \epsilon_{t+h}^{h} \tag{5}$$

Impulse Responses (IR) for the *shock event* are directly computed via OLS for each period in the estimation horizon. Additional meta-topic and/or behavior events can be added as controls in the linear projection, as well as the count variables in the vector of controls, x_t. Estimated IR are given by $\hat{IR}(h) = \{\hat{\beta_h}\}$, where $\hat{\beta}$ are the h step-ahead estimated coefficients. Confidence bands, based on heteroskedasticity robust standard errors, are reported at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range.

4 Results

Results in this paper focus on the high-frequency effects of selected events on stock market uncertainty. Section 4.1 presents the impulse responses of different behavior events estimated as in Equation 5 using the change in the VIX, Δvix_{t+h} as dependent variable. In Section 4.2 behavior events are replaced by meta-topic events. Finally, Section 4.3 combines both types of events by allowing for interaction terms in Equation 4. For results from a similar analysis at the daily frequency using the EPU index as uncertainty measure, see Appendix C.

4.1 Impact of behavior events on market volatility

The objective of the first part of this section is to test if less frequent events originating from observations in the tails of the count variable distribution, such as "more than two tweets/retweets in a five-minute interval", can be interpreted as uncertainty shock as proposed in Kozeniauskas et al. (2018). To do this, I estimate regression model from Equation 5 with Δvix_{t+h} as dependent variable and behavior events as independent variables. These events are generated as in Equation 1 using the following conditions: "$total\ count > threshold$" with $threshold = \{0, 1, 2\}$ and "$retweeted\ count > percentile$" with $percentile = \{50, 60, 80\}$. Each behavior event is estimated independently without the inclusion of controls. Figure 2 presents estimated responses to the events mentioned above, with h, set to 60 periods (5 hours).

Figure 2 panel a) shows the estimated effect of at least one tweet or retweet, ($total\ count > 0$). There is a medium size[15] positive effect in the period between 1.25 and 3.3 hours after the event, significant at the 10% level. The effect achieves its peak after 2.5 hours with a magnitude equal to 0.023 pp. The response's small hump form implies a delayed and short-lived impact on the options market. A break-down analysis of the partial contribution of each component of *total count* in figure B.1 in appendix B reveals that the effect observed in panel a) on Figure 2 is mainly driven by the content produced by Trump himself (the tweets), rather than the content he retweeted.

The left panels of Figure 2 show the progression in the magnitude of the estimated coefficients as one defines the event's condition from a point further to the right in the distribution of total counts. As the event becomes less likely, response's peaks increase in magnitude from 0.023 pp in panel a) to around 0.057 pp in panel c), after two hours. The confidence bands widen accordingly as the number of events reduces and the standard deviation of the point estimates increases.

The right panels in figure 2 depict a similar pattern for three different behavior events based on the retweeted count. As the percentile threshold increases, meaning increasing the number of times a tweet or retweet should be retweeted to satisfy the event's condition, response's peak almost double from 0.019 pp in panel d) to 0.037 pp in panel f). This progression implies that as posts become viral (massively retweeted) they have a larger impact on uncertainty.

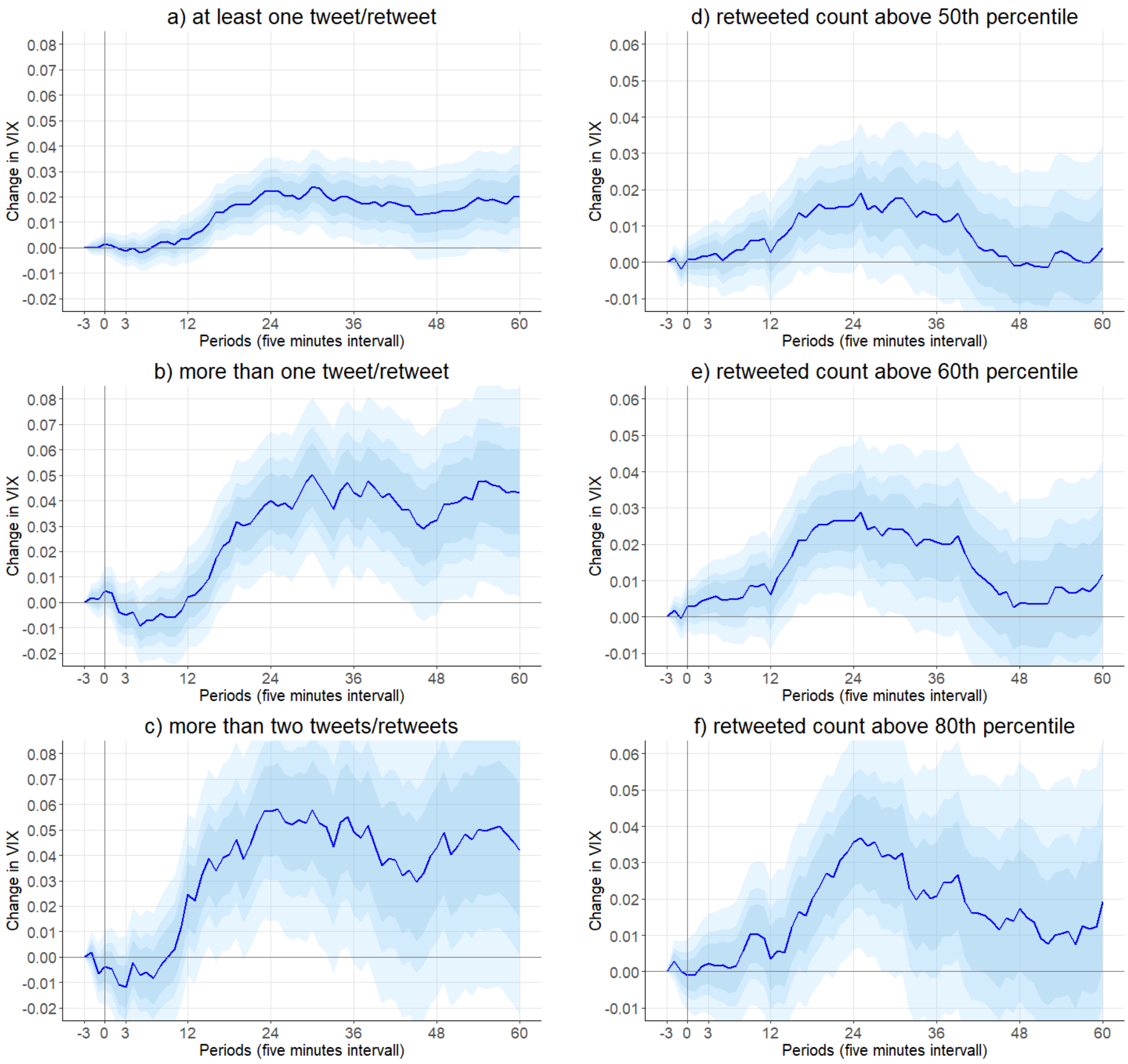
Altogether, these results suggest that one can interpret unexpected changes in Trump's tweet behavior or follower's behavior as uncertainty shocks in the options market, and the magnitude of their effects increases as the underlying event becomes less likely.

4.2 Impact of meta-topic events on market volatility

The second set of results focuses exclusively on the content of the tweets, regardless of the form (tweets or retweets), the frequency (number of counts), or the social network reaction (in terms of favorite or retweeted count). Figure 3 presents the impulse responses of five meta-topic events corresponding to economic policy

[15] Based on a Cohen's d value of 0.54.

Figure 2: Responses of the change in the VIX to selected behavior events



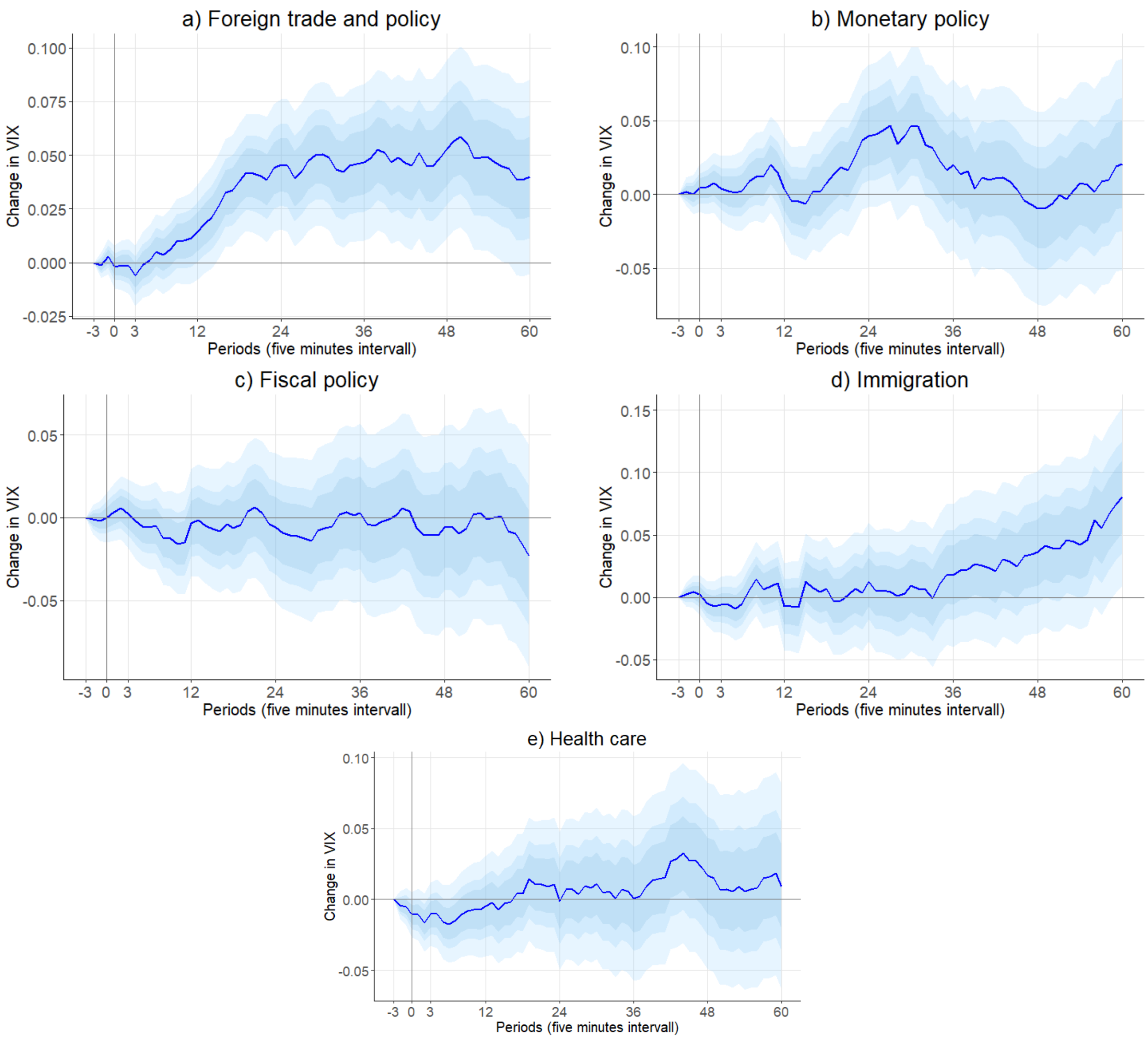
Note: This figure plots the estimated coefficients β_h in Equation 5 for selected behavior events against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors. Sample period 31.12.2015 23:11 CST to 21.10.2019 12:31 CST.

narratives regarding *foreign trade and foreign policy*, *monetary policy*, *fiscal policy*, *immigration policy*, and *health care policy*. Impulse responses for each meta-topic event are estimated as in Equation 5 using one event as the shock event and the remaining four as controls but excluding count controls. These broader narratives are composed of a group of smaller interrelated narratives, implied by the estimated topic. It does not necessarily mean that their effect on uncertainty follows the same direction so that the β_h coefficients plotted in Figure 3 represent the average effect over the meta-topic constituents.

Panel a) in figure 3 presents the response of the change in the VIX to the meta-topic event *foreign policy and trade*. This response smoothly builds up and becomes significant at the 10% level after one hour and 15 minutes. It remains near to 0.05 pp for around two hours, reaching its maximum level of around 0.06 pp. After four hours and 10 minutes (or 50 periods), it slowly decades and becomes not statistically different from zero at the end of the horizon. This result supports the findings reported in Fendel et al. (2020), suggesting that the narrative about Trump's style of dealing with foreign policy and international trade issues has a significant negative effect on options market volatility.

An analysis of the effect of the constituents for this meta-topic (figure B.2 in appendix B) suggest that the aggregate positive response is mostly driven by *topic 7* with a maximum effect of 0.17 pp after 38 periods, *topic 10* with roughly 0.12 pp after 38 periods, and *topic 36* with 0.075 after 25 periods. These maximum estimates are significant at the 1%, 5%, and 10% level, respectively. The other constituent of this meta-topic, *topic 16*, display an overall negative, but it is not statistically significant. Since all four topics share some of the same top-30 words but they differ in the rank of these words in each topic, it is not possible to say which topic specifically identify a specific well-known narrative such as the *"trade war with China"*, or *"tentative agreement with China regarding trade"*. However, the idea of using a topic model approach allows us to identify the overall story even when it is told with different words, so that narratives implying trade policy uncertainty dominates the aggregate response, over narratives such as *"successful trade deal"*, implied

Figure 3: Responses of the change in the VIX to selected meta-topic events



Note: This figure plots the estimated coefficients β_h in Equation 5 for selected meta-topic events against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors. Sample period 31.12.2015 23:11 CST to 21.10.2019 12:31 CST.

in topic 16, which dampens the aggregate effect over the forecast horizon. Overall, these results support previous findings in Fendel et al. (2020), suggesting that Donald Trump's style of dealing with foreign policy and international trade issues generate market volatility.

The propagation mechanism of the narrative in panel a) is extremely fast since it takes only one hour and 15 minutes to disseminate and generate an effect in the market. Two factors can explain the timing of this response. First, as Shiller (2019a) suggest, narratives spread faster if it is told by or involves a celebrity. Second, the ability of a tweet to be retweeted with one click to a large group of people intermediately[16].

Panel b) and c) in figure 3 present the estimated effect of narratives regarding monetary and fiscal policies. Responses to both of these meta-topic events are not statistically significant at the 10% level during the whole horizon. However, one of the two constituents of the meta-topic *monetary policy*, specifically *topic 14* (figure B.3 in appendix B), is significant at the 10% level for 30 minutes, two hours after the occurrence of the topic event. The response to the *topic 14* event reaches its maximum value of about 0.075 pp after 28 periods (2 hours and 20 minutes). This topic appears to be the driving force behind the response to the*monetary policy* event since its dynamics closely resembles the dynamics of the meta-topic, and it includes most of the keywords directly related to monetary policy[17]. The response to the *monetary policy* meta-topic event fits well the narrative on Trump's threats to central bank independence already documented in Bianchi et al. (2019). This study shows that Trump's advocacy of lower interest rates via Twitter has a significant negative effect on Fed fund futures contracts. The results discussed in this section suggest that narratives regarding Trump's position on monetary policy issues not only affect Fed funds futures but also S&P 500 options prices.

The last two panels of figure 3 show the cumulative effect of meta-topics regarding *immigration policy* and *health-care policy*. The immigration narrative has been a workhorse for President Trump since he

[16]Table 1 shows that a tweet can be retweeted over 160,000 times in a five-minute interval.
[17]The top-30 keywords for topic 14 in, descending order, are: *low, high, year, rate, unemployment, job, good, stock_market, hit, record, economy, time, price, consumer, fall, growth, fed, strong, business, level, confidence, big, economic, interest, GDP, record_high, u.s, point, increase, all-time.*

campaigned for the republican candidacy in 2015. The main narratives implied in this meta-topic include building a wall with Mexico and revoking the DACA program. Panel d shows that the response to this event wanders around zero for the first three hours after the event, and slowly builds up after that. It becomes significantly different than zero in the last two periods (or after 4 hours and 50 minutes) and achieves its maximum value of 0.08 in the last period. This response reflects the concerns of 58 CEOs that warn Trump about the negative consequences of a restrictive immigration policy[18]. The order in which the response to a meta-topic event becomes statistically significant may reflect the importance rank in which market participants order Trump's policy related narratives, being *foreign trade and policy* first, *monetary policy* second, and *immigration policy* last. Finally, the VIX response to *health-care* meta-topic events, as well as its components, are not significantly different from zero at any time horizon.

4.3 Interaction between meta-topics and behavior events

In this final section, I review in detail the results found in the last two results sections by estimating responses to behavior events related to high retweeted activity and the meta-topic events at three relevant periods in the forecast horizon, namely 15 minutes, 2 hours, and 5 hours, and including count controls. Additionally, I also allow for interactions between both types of events controlling for the number of tweets. Equation 6 summarizes the regression model for this section.

$$\begin{aligned}\Delta y_{t+h} &= \alpha_h + \sum_{j=1}^{J} \beta_{j,h} event_{m,t} + \gamma_h event_{b,t} \\ &+ \sum_{j=1}^{J} \phi_{j,h} event_{m,t} \times event_{b,t} + \lambda x_t + \epsilon^h_{t+h}\end{aligned} \tag{6}$$

Table 4 presents estimates for different specifications of regression Equation 6. As observed in figures 2 and 3, there are no significant meta-topic or behavioral event coefficients in regressions (1) and (2), indicating no immediate effect of Trump's tweets in market volatility. The response to the behavior event *retweet count above* 60^{th} *percentile* in Equation (3) is positive and significant; however, the interactions of this event with meta-topic events are not significant.

Table 4: Cumulative effect of main counts and economic related meta-topic events on change in VIX

	15 minutes			2 hours				5 hours		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	-0.0001	-0.0001	-0.0001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.0003)	(0.0001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Foreign policy and trade	-0.004		-0.002	0.037*	0.033*		0.035	0.034		0.039
	(0.009)		(0.012)	(0.019)	(0.020)		(0.022)	(0.029)		(0.033)
Monetary policy	0.005		0.010	0.032	0.028		-0.001	0.015		-0.013
	(0.014)		(0.019)	(0.030)	(0.030)		(0.033)	(0.044)		(0.049)
Fiscal policy	0.004		0.004	-0.014	-0.016		-0.015	-0.029		-0.031
	(0.013)		(0.016)	(0.028)	(0.028)		(0.030)	(0.041)		(0.045)
Immigration	-0.004		-0.011	0.004	0.001		-0.022	0.075*		0.040
	(0.014)		(0.021)	(0.029)	(0.030)		(0.038)	(0.044)		(0.057)
Health care	-0.009		-0.004	-0.009	-0.011		-0.009	0.004		0.017
	(0.014)		(0.019)	(0.030)	(0.030)		(0.034)	(0.044)		(0.051)
Retweeted > 60^{th}p.		0.012	0.016*			0.004			-0.010	
		(0.009)	(0.008)			(0.019)			(0.029)	
Retweeted > 80^{th}p.		-0.006				0.020	-0.003		0.017	-0.027
		(0.012)				(0.025)	(0.025)		(0.038)	(0.037)
Foreign policy and trade			-0.013				0.007			-0.011
× Retweeted > 60^{th}/80^{th}p.			(0.019)				(0.048)			(0.072)
Monetary policy			-0.018				0.162**			0.153
× Retweeted > 60^{th}/80^{th}p.			(0.028)				(0.075)			(0.112)
Fiscal policy			-0.005				0.021			0.020
× Retweeted > 60^{th}/80^{th}p.			(0.028)				(0.081)			(0.121)
Immigration			0.005				0.061			0.104
× Retweeted > 60^{th}/80^{th}p.			(0.028)				(0.062)			(0.093)
Health care			-0.016				0.006			-0.035
× Retweeted > 60^{th}/80^{th}p.			(0.028)				(0.072)			(0.107)
Total count	-0.002	-0.003	-0.003	0.009*		0.010**	0.009*	0.006	0.012	0.008
	(0.002)	(0.002)	(0.003)	(0.005)		(0.005)	(0.005)	(0.008)	(0.007)	(0.008)
Tweet count					0.014*					
					(0.008)					
Retweet count					0.005					
					(0.007)					
Observations	241,663	241,663	241,663	241,630	241,630	241,630	241,642	241,606	241,606	241,606
Adjusted R^2	-0.00002	0.00000	-0.00002	0.00000	0.00000	0.00002	0.00003	0.00001	0.00000	-0.00000

Note: Estimated coefficients from Equation 6 using 5-minutes frequency data for the VIX. Robust standard errors are shown in parenthesis. Significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample period 31.12.2015 23:11 CST to 21.10.2019 12:31 CST. Percentile 60^{th} is used for interaction terms in regression (3). Percentile 80^{th} is used for interaction terms in regressions (7) and (10).

[18]This was an open letter signed by Tim Cook among other CEOs on August 24, 2018.

Regressions (4) and (5) present the cumulative effect of meta-topic events two hours after they occur, controlling for the number of posts. The effect of the *foreign policy and trade* meta-topic event is slightly lower than the uncontrolled effect reported in figure 3, but still significant at the 10 % level. Other meta-topic events remain not significant. The number of posts, or total count, is significant at this horizon and is mainly driven by tweet count, while the retweet count remains not significant. Behavior events in (6) regarding retweeted count above the 60^{th} or 80^{th} percentile are not statistically significant after controlling for the number of posts. From regression (7) one can observe that only the interaction term between *monetary policy* and *retweeted* above 80^{th} percentile is significant at the 5% level. This suggests that narratives regarding monetary policy, which are heavily disseminated by the retweet channel, increase market uncertainty by 0.162 pp, after controlling for the number of counts and other events.

Regressions (8), (9), and (10) reveal that the effect of the estimated events is short-lived. Only narratives regarding immigration are significant at the 10% level five hours after the corresponding meta-topic event occurs when controlling for total counts.

5 Conclusions

Economic policy narratives extracted from Trump's Twitter data using machine learning, without any sort of political bias in their construction, explain to an extent a fraction of the variation on stock market uncertainty represented by the VIX. Identified Trump's tweet behavior events also reveal some variation in the VIX. Combined, these results provide evidence for significant high-frequency market uncertainty movements after presidential announcements made on Twitter. Economic policy narratives about foreign policy, trade, and immigration by themselves lead the effect on uncertainty, while the monetary policy narrative is only significant in combination with high levels of retweeting activity. These results also provide some hints on how economic narratives may work: An original message is successfully spread through a social media channel, the general public identifies the implied narrative and associates it with similar ones, if a narrative is of general interest, it triggers a spreading mechanism, given in this case (but not only) by the retweeted channel. This process repeats itself until it reaches market participants, who may include this information when forming their expectations regarding future economic policy. This process can take between one and five hours for significant meta-topic events; one can expect a market reaction only after this time. This paper also explores the long-term effects of economic policy narratives by using the change in the EPU index as an uncertainty measure, but the evidence for these effects is inconclusive.

The policy implications of the results presented in this paper should not be constrained to the behavior of a particular politician (here Mr. Trump); instead, it should call policymakers, independent of their political affiliation, to be aware of the negative economic impact of uncontrolled social network activity. As social networks become more popular among politicians as the preferred channel to connect with the general public, these effects may become more pronounced, and policymakers should, to some extent, be accountable for the social and economic consequences of their social network activity.

References

Amengual, Dante et al. (2018). "Resolution of policy uncertainty and sudden declines in volatility". In: *Journal of Econometrics* 203.2, pp. 297–315.

Azqueta-Gavaldón, Andrés (2020). "Causal inference between cryptocurrency narratives and prices: Evidence from a complex dynamic ecosystem". In: *Physica A: Statistical Mechanics and its Applications* 537, p. 122574.

Baker, Scott R et al. (2016). "Measuring economic policy uncertainty". In: *The quarterly journal of economics* 131.4, pp. 1593–1636.

Baker, Scott R et al. (2019). *Policy news and stock market volatility.* Working Paper No. w25720. National Bureau of Economic Research.

Beechey, Meredith J et al. (2009). "The high-frequency impact of news on long-term yields and forward rates: Is it real?" In: *Journal of Monetary Economics* 56.4, pp. 535–544.

Belo, Frederico et al. (2013). "Government spending, political cycles, and the cross section of stock returns". In: *Journal of Financial Economics* 107.2, pp. 305–324.

Bialkowski, Jedrzej et al. (2008). "Stock market volatility around national elections". In: *Journal of Banking & Finance* 32.9, pp. 1941–1953.

Bianchi, Francesco et al. (2019). *Threats to Central Bank Independence: High-Frequency Identification with Twitter.* Working Paper No. w26308. National Bureau of Economic Research.

Bittlingmayer, George (1998). "Output, stock volatility, and political uncertainty in a natural experiment: Germany, 1880–1940". In: *The Journal of Finance* 53.6, pp. 2243–2257.

Blei, David M et al. (2003). "Latent dirichlet allocation". In: *Journal of machine Learning research* 3.Jan, pp. 993–1022.

Bomfim, Antulio N (2003). "Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market". In: *Journal of Banking & Finance* 27.1, pp. 133–151.

Burggraf, Tobias et al. (2020). "Political news and stock prices: evidence from Trump's trade war". In: *Applied Economics Letters* 27.18, pp. 1485–1488.

Bybee, Leland et al. (2020). *The structure of economic news*. Working Paper No. w26648. National Bureau of Economic Research.

Clements, Adam et al. (2007). "S&P 500 implied volatility and monetary policy announcements". In: *Finance Research Letters* 4.4, pp. 227–232.

Colonescu, Constantin et al. (2018). "The Effects of Donald Trump's Tweets on US Financial and Foreign Exchange Markets". In: *Athens Journal of Business & Economics* 4.4, pp. 375–388.

Fan, Rui et al. (2020). "Social media, political uncertainty, and stock markets". In: *Review of Quantitative Finance and Accounting*, pp. 1–17.

Fendel, Ralf et al. (2020). "Political News and Stock Prices: Evidence from Trump's Trade War". In: *Forthcoming, Applied Economics Letters* 27.18, pp. 1485–1488.

Gemmill, Gordon (1992). "Political risk and market efficiency: tests based in British stock and options markets in the 1987 election". In: *Journal of Banking & Finance* 16.1, pp. 211–231.

Gilbert, Thomas et al. (2017). "Is the intrinsic value of a macroeconomic news announcement related to its asset price impact?" In: *Journal of Monetary Economics* 92, pp. 78–95.

Goodell, John W et al. (2013). "US presidential elections and implied volatility: The role of political uncertainty". In: *Journal of Banking & Finance* 37.3, pp. 1108–1117.

Graham, Michael et al. (2003). "Relative importance of scheduled macroeconomic news for stock market investors". In: *Journal of Economics and Finance* 27.2, pp. 153–165.

Griffiths, Thomas L et al. (2004). "Finding scientific topics". In: *Proceedings of the National academy of Sciences* 101.suppl 1, pp. 5228–5235.

Hanna, Alan J et al. (2020). "News media and investor sentiment during bull and bear markets". In: *The European Journal of Finance* 26.14, pp. 1377–1395.

Hornik, Kurt et al. (2011). "topicmodels: An R package for fitting topic models". In: *Journal of statistical software* 40.13, pp. 1–30.

Jordà, Òscar (2005). "Estimation and inference of impulse responses by local projections". In: *American economic review* 95.1, pp. 161–182.

Kelly, Bryan et al. (2016). "The price of political uncertainty: Theory and evidence from the option market". In: *The Journal of Finance* 71.5, pp. 2417–2480.

Kinyua, Johnson K et al. (2021). "An analysis of the impact of President Trump's tweets on the DJIA and S&P 500 using machine learning and sentiment analysis". In: *Journal of Behavioral and Experimental Finance* 29, p. 100447.

Klaus, Jürgen et al. (2020). "Measuring Trump: The Volfefe Index and its impact on European financial markets". In: *Finance Research Letters* 38, p. 101447.

Kozeniauskas, Nicholas et al. (2018). "What are uncertainty shocks?" In: *Journal of Monetary Economics* 100, pp. 1–15.

Lapp, John S et al. (2012). "The impact of economic news on expected changes in monetary policy". In: *Journal of Macroeconomics* 34.2, pp. 362–379.

Larsen, Vegard H et al. (2020). "News-driven inflation expectations and information rigidities". In: *Journal of Monetary Economics*.

Lee, Jieun et al. (2019). "The impacts of public news announcements on intraday implied volatility dynamics". In: *Journal of Futures Markets* 39.6, pp. 656–685.

Li, Jinliang et al. (2006). "Presidential election uncertainty and common stock returns in the United States". In: *Journal of Financial Research* 29.4, pp. 609–622.

McBeth, Mark K et al. (2018). "Media narratives versus evidence in economic policy making: The 2008–2009 financial crisis". In: *Social Science Quarterly* 99.2, pp. 791–806.

Newman, David et al. (2009). "Distributed algorithms for topic models." In: *Journal of Machine Learning Research* 10.8.

Pantzalis, Christos et al. (2000). "Political elections and the resolution of uncertainty: the international evidence". In: *Journal of banking & finance* 24.10, pp. 1575–1604.

Pástor, L'uboš et al. (2013). "Political uncertainty and risk premia". In: *Journal of financial Economics* 110.3, pp. 520–545.

Piñeiro-Chousa, Juan Ramón et al. (2016). "Examining the influence of stock market variables on microblogging sentiment". In: *Journal of Business Research* 69.6, pp. 2087–2092.

Schnaubelt, Matthias et al. (2020). "Separating the signal from the noise–financial machine learning for Twitter". In: *Journal of Economic Dynamics and Control* 114, p. 103895.

Shiller, Robert J (2017). "Narrative economics". In: *American Economic Review* 107.4, pp. 967–1004.

— (2019a). *Narrative economics: How stories go viral and drive major economic events.* Princeton University Press.

— (2019b). *Narratives about Technology-Induced Job Degradations Then and Now.* Working Paper No. w25536. National Bureau of Economic Research.

— (2020). "Popular Economic Narratives Advancing the Longest US Expansion 2009-2019". In: *Journal of Policy Modeling* 42.4, pp. 791–798.

Stevens, Keith et al. (2012). "Exploring topic coherence over many models and many topics". In: *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning.* Association for Computational Linguistics, pp. 952–961.

Yang, Steve Y et al. (2015). "Twitter financial community sentiment and its predictive relationship to stock market movement". In: *Quantitative Finance* 15.10, pp. 1637–1656.

Appendix

A Topic model Estimation and optimal number of topics

A.1 Preprocessing

I drop stop-words and special characters such as emojis, links, and symbols. The pre-procesing is completed by defining collocations, or set of terms that come together, such as "Hillary Clinton", at least 25 times in the corpus, and reducing terms to its lemma.

A.2 Estimation

The generative model for the LDA, as described in Blei et al. (2003), consists of the following steps.

1. Determine term distribution, β, for each topic, which is given by:

$$\beta \sim Dirichlet(\delta)$$

2. Determine proportions, θ , of the topic distribution for each document, w:

$$\theta \sim Dirichlet(\alpha)$$

3. For each of the N words w_i:

   (a) Choose a topic $z_i \sim Multinomial(\theta)$.

   (b) Choose a word w_i from a multinomial probability distribution conditioned on the topic z_i : $p(w_i|z_i,\beta)$.

This model is estimated using the Gibbs sampling, as proposed in Griffiths et al. (2004). Draws from the posterior distribution $p(z|w)$ are obtained by sampling from:

$$p(z_i = K|w, z_i) \propto \frac{n^{(j)}_{-i,K} + \delta}{n^{(.)}_{-i,K} + V\delta} \frac{n^{(d_i)}_{-i,K} + \alpha}{n^{(d_i)}_{-i} + k\alpha} \tag{A.1}$$

The dot (.) implies that summation over the index is performed. The hyperparameter α, prior parameter for the distribution of topics over documents, is set to 0.1, and δ, prior parameter for the distribution of words over topics, is set to 0.1. The optimal number of topics $K = K^*$ will be defined in the next section.

Estimates $\hat{\beta}$ and $\hat{\theta}$ are given by:

$$\hat{\beta}^{(j)}_K = \frac{n^{(j)}_K + \delta}{n^{(.)}_K + V\delta} \qquad \hat{\theta}^{(d)}_K = \frac{n^{(d)}_K + \alpha}{n^{(d)} + k\alpha} \tag{A.2}$$

A.3 Model evaluation and parameter selection

Optimal model is selected based on maximum mean coherence and median coherence in the region where perplexity is strictly below its average. The perplexity measure, based on Newman et al. (2009), evaluates how well a probability model predicts a sample based on held-out data, therefore a lower perplexity model is desirable.

$$Perplexity(w) = exp\left\{-\frac{log(p(w))}{\sum_{d=1}^{D}\sum_{j=1}^{V} n^{(jd)}}\right\} \tag{A.3}$$

The log-likelihood is given by:

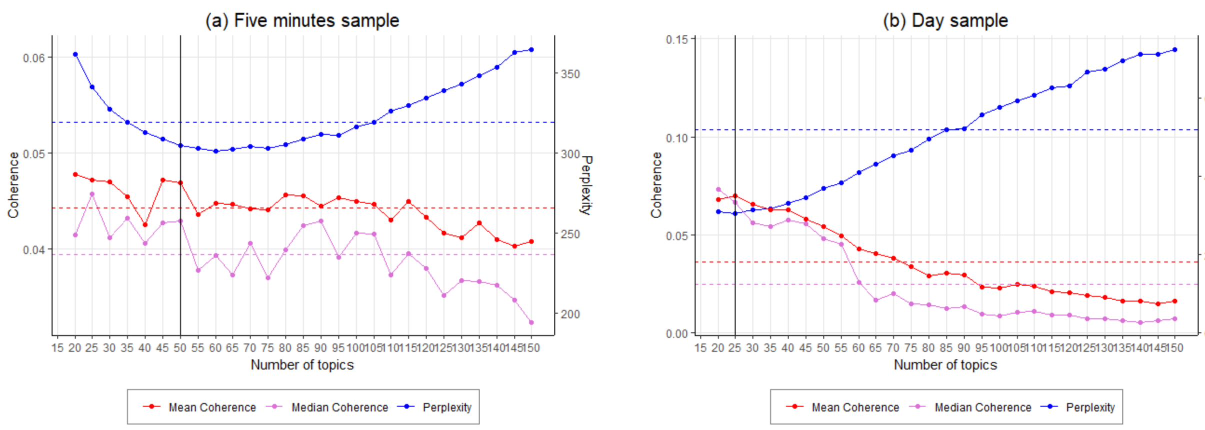
$$log(p(w)) = \sum_{d=1}^{D}\sum_{j=1}^{V} n^{(jd)} log\left[\sum_{K=1}^{k} \theta^{(d)}_k \beta^{(d)}_k\right] \tag{A.4}$$

Topic coherence provides a rank for topic models by measuring the degree of semantic similarity between high scoring words within a set of topics. These measurements help to identify topics that are semantically interpretable topics and topics that are artifacts of statistical inference Stevens et al. (2012). The coherence measure proposed is based on co-occurrences of word pairs within the corpus used to train the topic model. Given an ordered list of words $T_k = w_1, \ldots, w_n$, for each resulting topic $k \in K^*$, the UMass-coherence is defined as:

$$Coherence_{UMass}(T_k) = \sum_{m=2}^{M} \sum_{m-1}^{l} log \frac{p(w_m, w_l) + \frac{1}{D}}{p(w_l)} \tag{A.5}$$

The smoothing count $1/D$ is added to avoid calculating the logarithm of zero. These measures are calculated for a series of models with different values for K. Figure A.1 compare these alternative models in terms of perplexity and coherence.

Figure A.1: Selection of optimal number of topics



Note: dashed lines denoted the mean for each variable over all models.

The preferred model specifications are $K* = 50$ for 5-min sample and $K* = 40$ for the day sample. I choose $K* = 40$ instead of $K = 25$ for the day sample since a larger number of topics allow for more variety in the clustering section, and therefore a meta-topics distribution similar to the five-minutes sample. The resulting increase in perplexity and reduction in coherence is negligible.

A.4 Topic Clustering

Topics obtained from the preferred specification, $K = 50$ for 5-min sample, are hierarchical clustered based on the linguistic distance, here calculated based on Hellinger distance between topics, $Hd(\hat{\theta}_{k=i}, \hat{\theta}_{k=j})$:

$$Hd(\hat{\theta}_{k=i}, \hat{\theta}_{k=j}) = \frac{1}{2}\sqrt{\sum_{d=1}^{D}(\sqrt{\hat{\theta}_{k=i,d}}) - \sqrt{\hat{\theta}_{k=j,d}}))^2} \quad \text{,with } i \neq j \tag{A.6}$$

The clustering algorithm is given by the following sequence:

1. Generate initial clusters by joining two objects with minimal Hd, which means the *"closest"* ones, while all other objects remain apart.

2. Merge the two closest *clusters*, use the "unweighted pair-group average method", or UPGMA, of Sokal and Michener (1958), to calculate the dissimilarity measure between clusters. Assume there are two initial clusters A and B, such that its distance is given by:

$$d(A, B) = \frac{1}{|A||B|} \sum_{i=1,j=1} Hd(\hat{\theta}_{k=i}, \hat{\theta}_{k=j}), \quad \text{for } i \in A, j \in B \tag{A.7}$$

3. repeat step 2.

A.5 Results

Figure A.2: Topic dendrogramm five-minute sample, K=50

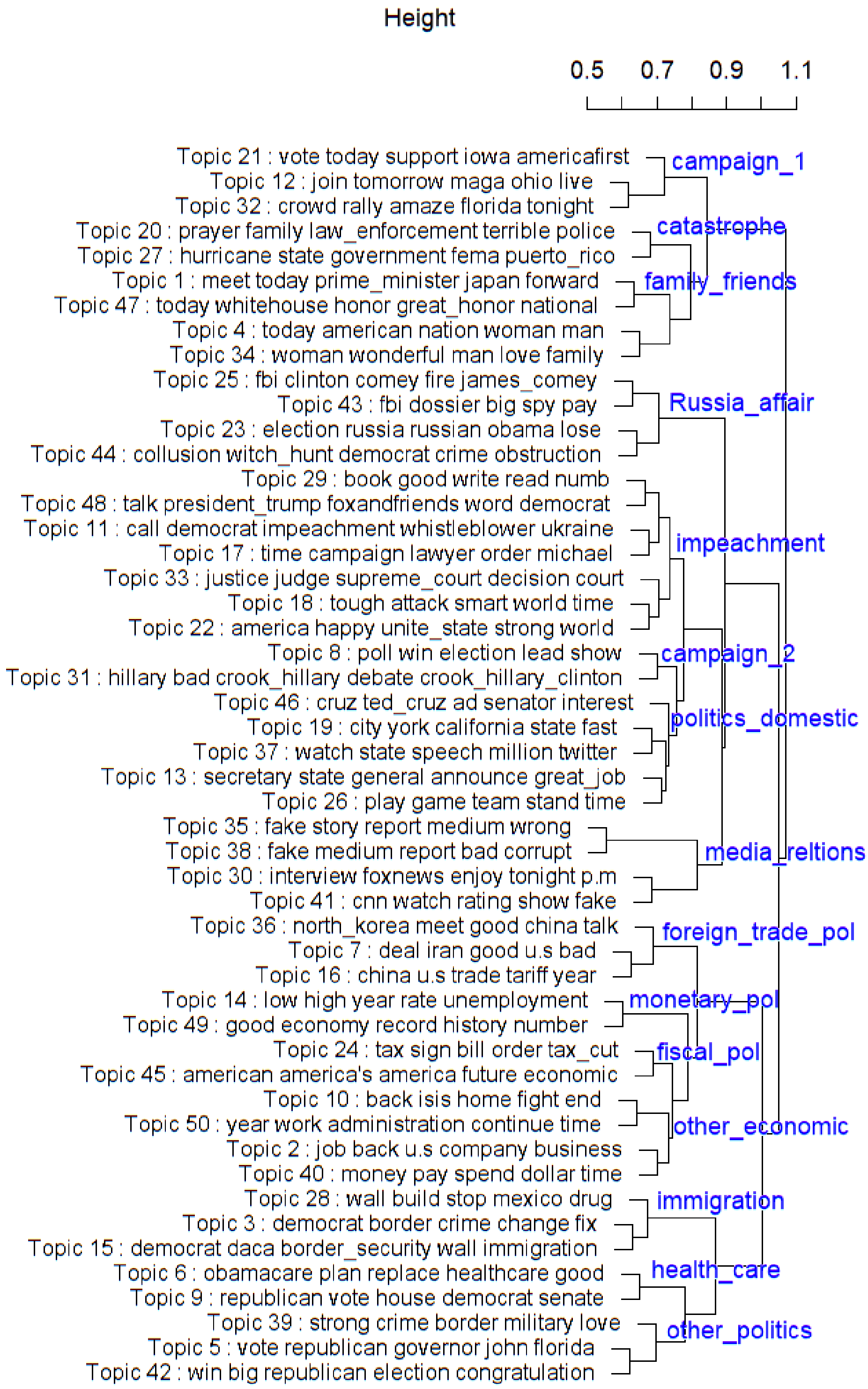


Table A.1: Meta-topics five-minute sample, top 10 words by topic

Label	Topic	Tokens
m_1 : Campaign	5	vote, republican, governor, john, florida, louisiana, kentucky, early, great_state, job
	8	poll, win, election, lead, show, number, good, point, big, republican_party
	12	join, tomorrow, maga, ohio, live, rally, ticket, florida, pennsylvania, tonight
	21	vote, today, support, iowa, americafirst, erictrump, poll, imwithyou, maga, hampshire
	31	hillary, bad, crook_hillary, debate, crook_hillary_clinton, rig, system, bernie, hillary_clinton
	32	crowd, rally, amaze, florida, tonight, back, speech, leave, texas, love
	39	strong, crime, border, military, love, vet, vote, endorsement, full, complete
	42	win , big, republican, election, congratulation, vote, victory, alabama, november, race
m_2 : Catastrophe	20	prayer, family, law_enforcement, terrible, police, thought, officer, victim, god_bless, shoot
	27	hurricane, state, government, fema, puerto_rico, safe, local, work, storm, ready
m_3 : Family and friends	1	meet, today, prime_minister, japan, forward, whitehouse, white_house, leader, friend, speak
	4	today, american, nation, woman, man, hero, live, honor, service, family
	34	woman, wonderful, man, love, family, beautiful, proud, miss, respect, forward
	47	today, whitehouse, honor, great_honor, national, flotus, presidential, congratulation, host, vp
m_4 : Investigations	11	call, democrat, impeachment, whistleblower, ukraine, statement, schiff, transcript, read, congress
	17	time, campaign, lawyer, order, michael, year, paul, break, agree, total
	18	tough, attack, smart, world, time, radical, terrorist, terrorism, swamp, change
	22	america, happy, unite_state, strong, world, stand, good, big, nation, speak
	23	election, russia, russian, obama, lose, collusion, democrat, committee, campaign, start
	25	fbi, clinton, comey, fire, james_comey, emails, lie, peter, mccabe, report
	29	book, good, write, read, numb, mark, foxandfriends, wonderful, happen, donald_trump
	33	justice, judge, supreme_court, decision, court, kavanaugh, case, white_house, federal, process
	43	fbi, dossier, big, spy, pay, crook_hillary, fake, campaign, russia, tomfitton
	44	collusion, witch_hunt, democrat, crime, obstruction, russia, hoax, dems, special
	48	talk, president_trump, foxandfriends, word, democrat, action, happen, hate, lot, israel
m_5 : Other politics	13	secretary, state, general, announce, great_job, act, john, director, chief, congratulation
	19	city, york, california, state, fast, school, happen, gun, sanctuary, give
	26	play, game, team, stand, time, win, flag, player, nfl, pay
	37	watch, state, speech, million, twitter, hear, voter, strongly, fraud, check
	46	cruz, ted_cruz, ad, senator, interest, candidate, presidential, fail, jeb, bush
m_6 : Media relations	30	interview, foxnews, enjoy, tonight, p.m, seanhannity, foxandfriends, watch, a.m, morning
	35	fake, story, report, medium, wrong, bad, write, source, fail_nytimes, york_time
	38	fake, medium, report, bad, corrupt, fact, dishonest, cover, enemy, totally
	41	cnn, watch, rating, show, fake, bad, foxnews, wow, total, bias
m_7 : Foreign policy	7	deal, iran, good, u.s, bad, mexico, work, world, agreement, big
and trade	10	back, isis, home, fight, end, syria, bring, war, year, turkey
	16	china, u.s, trade, tariff, year, farmer, unite_state, product, fair, treat
	36	north_korea, meet, good, china, talk, happen, nuclear, relationship, kim_jong, president_xi
m_8 : Monetary policy	14	low, high, year, rate, unemployment, job, good, stock_market, hit, record
	49	good, economy, record, history, number, job, set, big, military, strong
m_9 : Fiscal policy	24	tax, sign, bill, order, tax_cut, give, today, reform, promise, veteran
	45	american, america's, america, future, economic, policy, dream, whitehouse, worker, energy
m_{10} : Immigration	28	wall, build, stop, mexico, drug, border, southern_border, illegal, unite_state, criminal
	15	democrat, daca, border_security, wall, immigration, fight, dems, deal, shutdown, include
m_{11} : Health care	6	obamacare, plan, replace, healthcare, good, dems, disaster, repeal, republican
	9	republican, vote, house, democrat, senate, bill, dems, pass, support, give
m_{12} : Other economic	2	job, back, u.s, company, business, big, america, bring, usa, steel
	3	democrat, border, crime, change, fix , congress, law, problem, bad, crisis
	40	money, pay, spend, dollar, time, million, billion, year, u.s, save, cost
	50	year, work, administration, continue, time, fight, end, begin, month, back

Figure A.3: Topic dendrogramm day sample, K=40

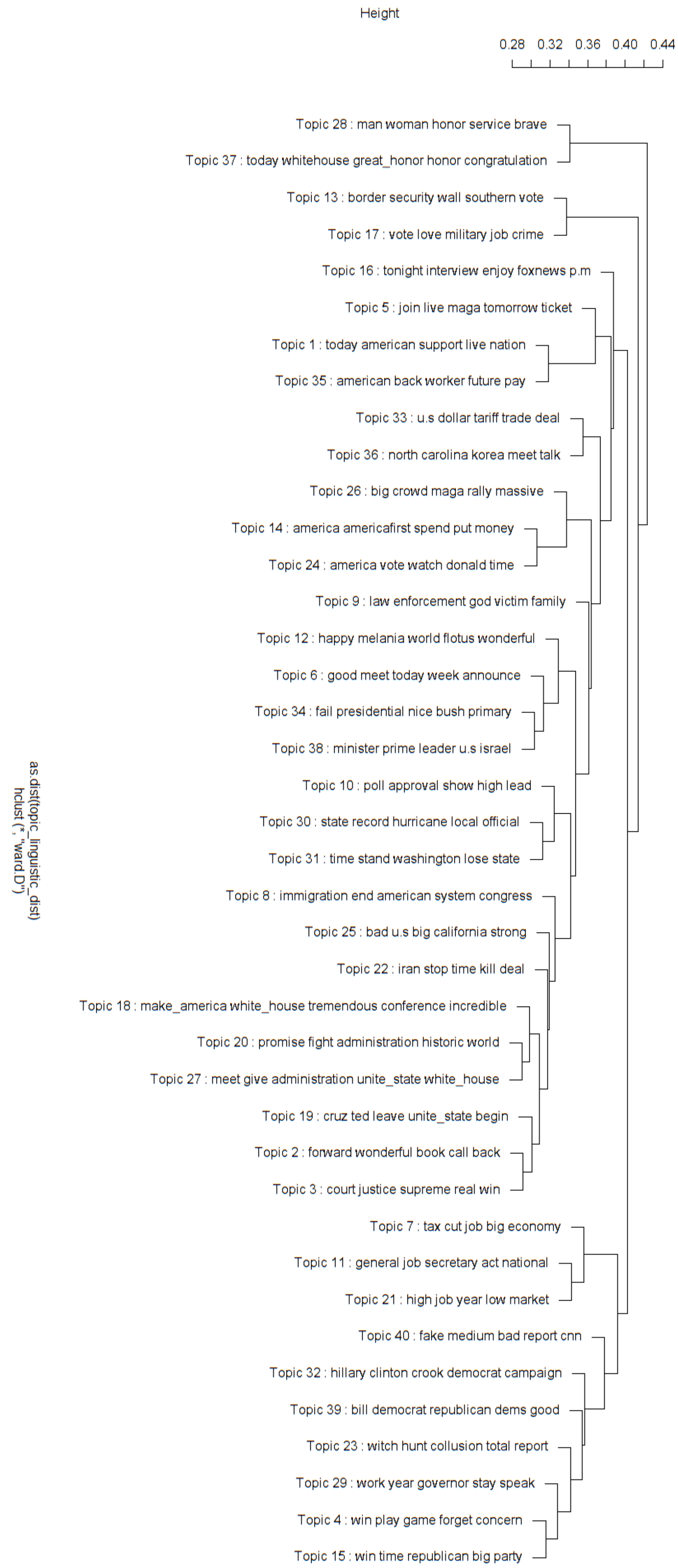


Table A.2: Meta-topics day sample, Top 10 words by topic

Label	Topic	Tokens
m_1 : Campaign	5	join , live , maga , tomorrow , ticket , florida , ohio , rally , love , https
	14	america , americafirst , spend , put , money , american , job , statement , bring , imwithyou
	24	america , vote , watch , donald , time , wisconsin , talk , million , foxandfriends , wiprimary
	26	big , crowd , maga , rally , massive , amaze , land , head , shortly , tremendous
m_2 : Catastrophe	9	law , enforcement , god , victim , family , prayer , bless , thought , incredible
	30	state , record , hurricane , local , official , fema , flood , ready , protect , continue
m_3 : Family and friends	6	good , meet , today , week , announce , team , mike , pence , support , state
	12	happy , melania , world , flotus , wonderful , celebrate , christmas , back , hope , place
	28	man , woman , honor , service , brave , today , air , happy , serve , birthday
	34	fail , presidential , nice , bush , primary , office , endorse , policy , conference , national
	37	today , whitehouse , great_honor , honor , congratulation , flotus , host , champion , national
m_4 : Investigations	2	forward , wonderful , book , call , back , begin , dakota , land , freedom
	3	court , justice , supreme , real , win , matt , find , mistake , man , growth
	23	witch , hunt , collusion , total , report , russian , comey , lie , fire , obstruction , mccabe
	32	hillary , clinton , crook , democrat , campaign , fbi , obama , win , election , big
m_5 : Other politics	4	win , play , game , forget , concern , proud , low , congratulation , agree , ivankatrump
	10	poll , approval , show , high , lead , political , rating , history , fake , state
	15	win , time , republican , big , party , lose , alabama , team , supporter , candidate
	18	make_america , white_house , tremendous , conference , incredible , safe , press , usmca , morning , progress
	19	cruz , ted , leave , unite_state , begin , york , call , fight , iowa , saudi
	20	promise , fight , administration , historic , world , hillary , visit , numerous , agree , important
	22	iran , stop , time , kill , deal , syria , respect , world , save , swamp , isis
	25	bad , u.s , big , california , strong , fire , turkey , law , fact , policy
	27	meet , give , administration , unite_state , white_house , destroy , center , intelligence , free , cost
	29	work , year , governor , stay , speak , continue , congratulation , closely , emergency , scott
	31	time , stand , washington , lose , state , york , debate , leave , read , post
	38	minister , prime , leader , u.s , israel , bring , presidential , part , recognize , sign
m_6 : Media relations	16	tonight , interview , enjoy , foxnews , p.m , seanhannity , fox , show
	40	fake , medium , bad , report , cnn , story , watch , campaign , wow , write
m_7 : Foreign policy	33	u.s, dollar, tariff, trade, deal, billion, build, military, farmer, strong
and trade	36	north, carolina, korea, meet, talk, south, leave, china, xi, trade
m_8 : Monetary policy	21	high, job, year, low, market, price, hit, good, stock, record
m_9 : Fiscal policy	7	tax, cut, job, big, economy, business, boom, good, economic, wealth
m_{10} : Immigration	8	immigration, end, american, system, congress, change, reform, protect, citizen
	13	border,security, wall, southern,vote, crime, work, democrat, happen, open
m_{11} : Health care	39	bill, democrat, republican, dems, good, sign, disaster, pass, obamacare, healthcare
m_{12} : Other economic	1	today , american , support , live , nation , year , community , safe , peace , life
	11	general , job , secretary , act , national , today , defense , announce , sign , protection
	17	vote , love , military , job , crime , total , vet , endorsement , senator , republican
	35	american , back , worker , future , pay , energy , steel , build , work , america's

B Impact of behavior events on market volatility: Extended results

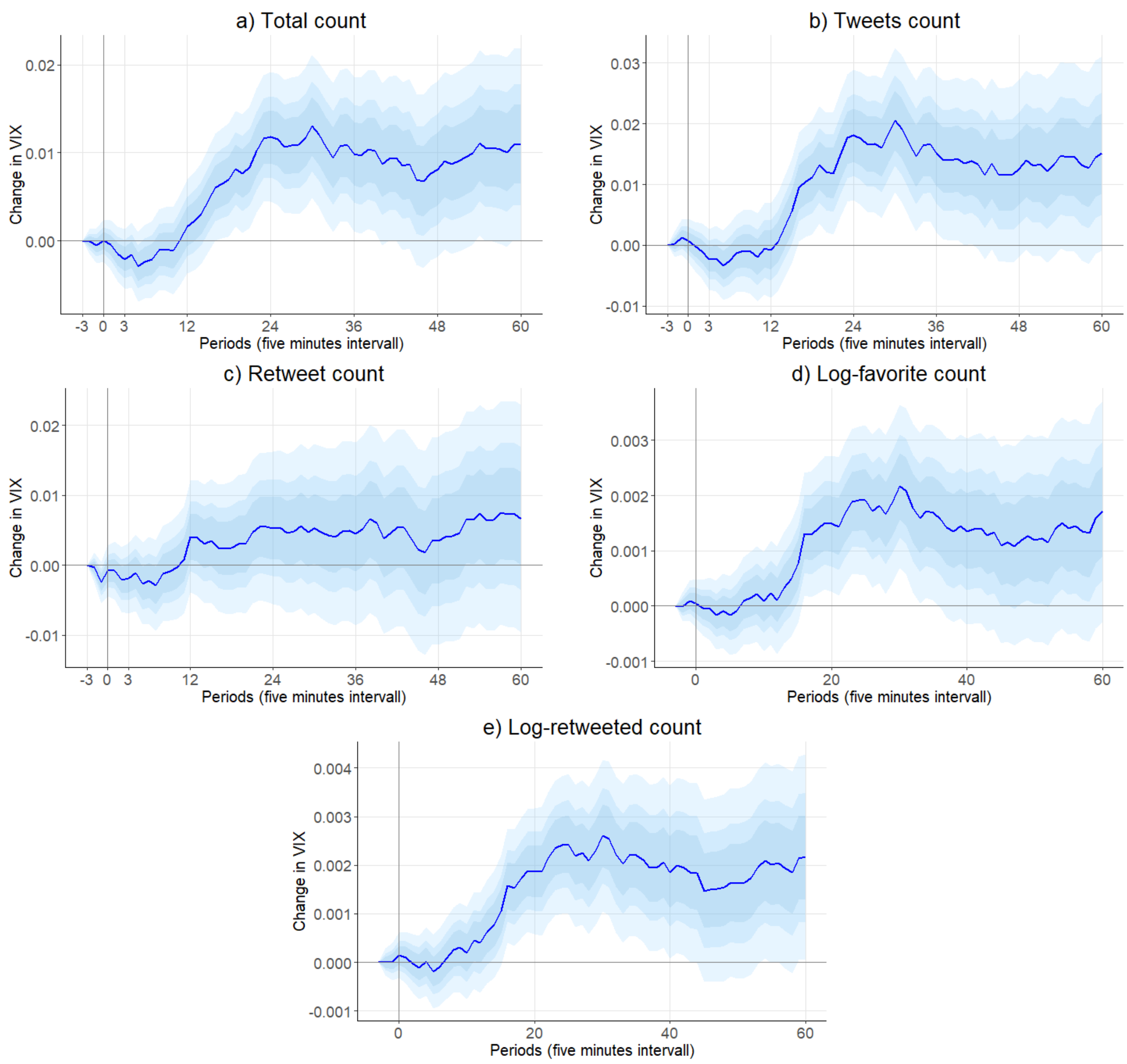
Table B.1: Summary statistics dependent variables

	VIX datasample						
	VIX level	Δvix_{t+3}	Δvix_{t+12}	Δvix_{t+24}	Δvix_{t+36}	Δvix_{t+48}	Δvix_{t+60}
Mean	15.87	-0.000096	-0.00024	-0.00045	-0.00067	-0.00089	-0.00112
S.d.	3.20	0.1555	0.2440	0.3345	0.4017	0.4555	0.4997
Obs.	241666	241663	241654	241642	241630	241618	241606

	EPU datasample						
	EPU level	Δepu_{t+1}	Δepu_{t+3}	Δepu_{t+7}	Δepu_{t+14}	Δepu_{t+21}	Δepu_{t+30}
Mean	95.22	-0.00006	0.000796	0.00177	0.00207	0.00268	0.00178
S.d.	50.70	0.6075	0.6511	0.6489	0.6874	0.6751	0.7147
Obs.	1413	1411	1409	1405	1398	1391	1382

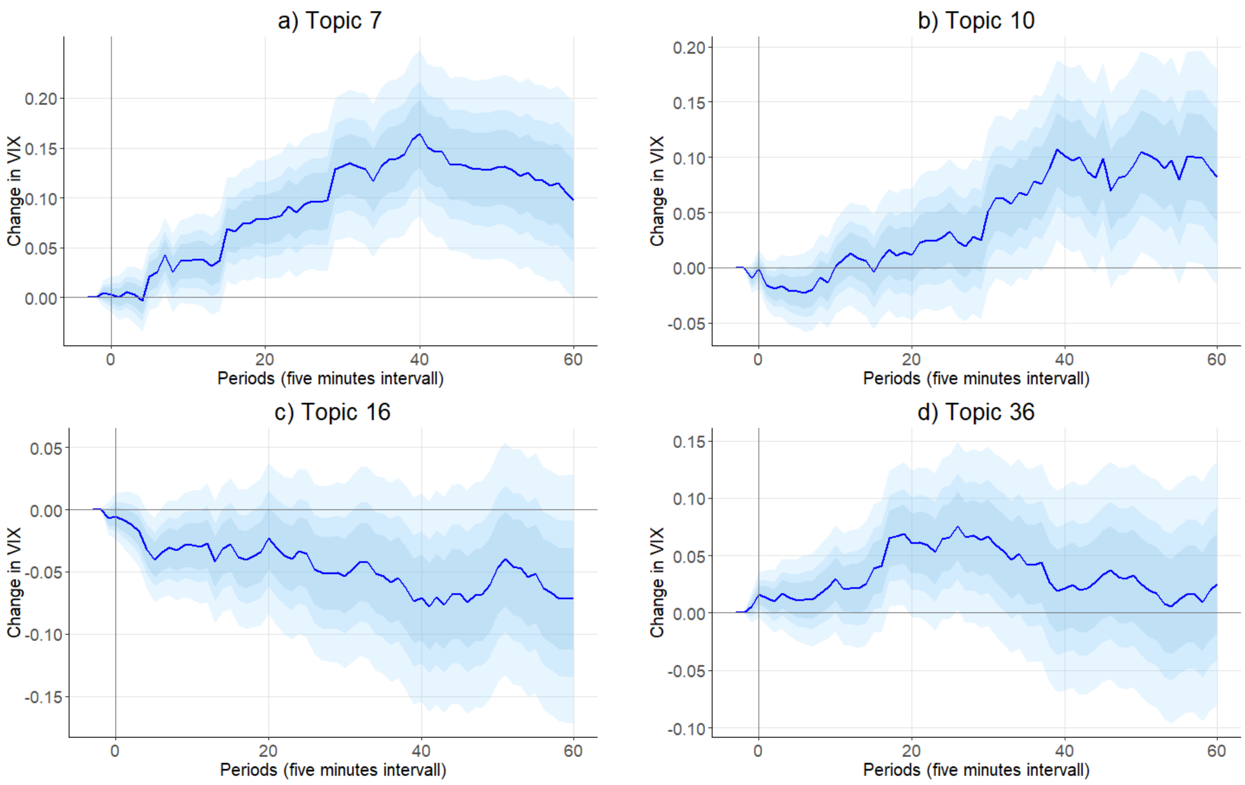
Note:The five-minutes VIX sample is composed of 241666 observations, while the EPU sample is composed of 1413 observations. For a definition of the coherence measure.

Figure B.1: Responses of the change in the VIX to of main counts



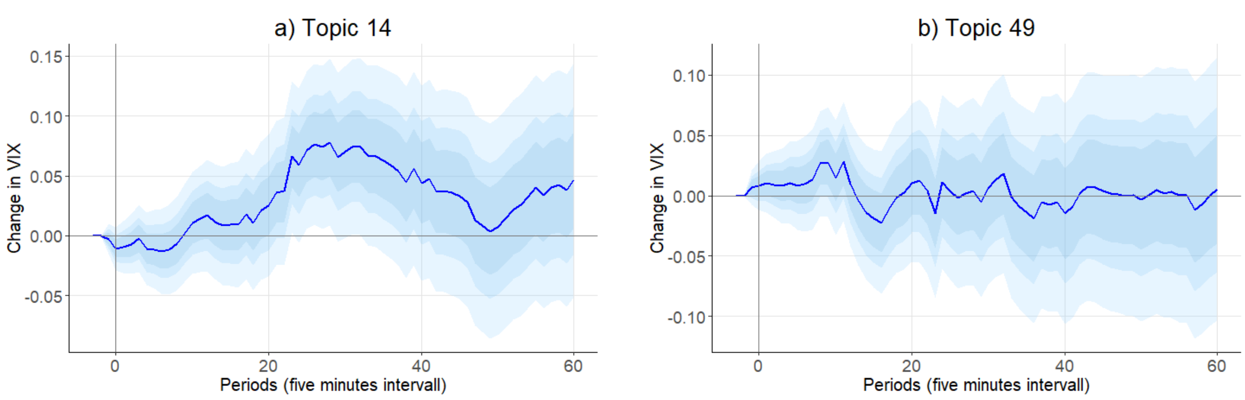
Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

Figure B.2: Responses of the change in the VIX to constituents of foreign policy and trade



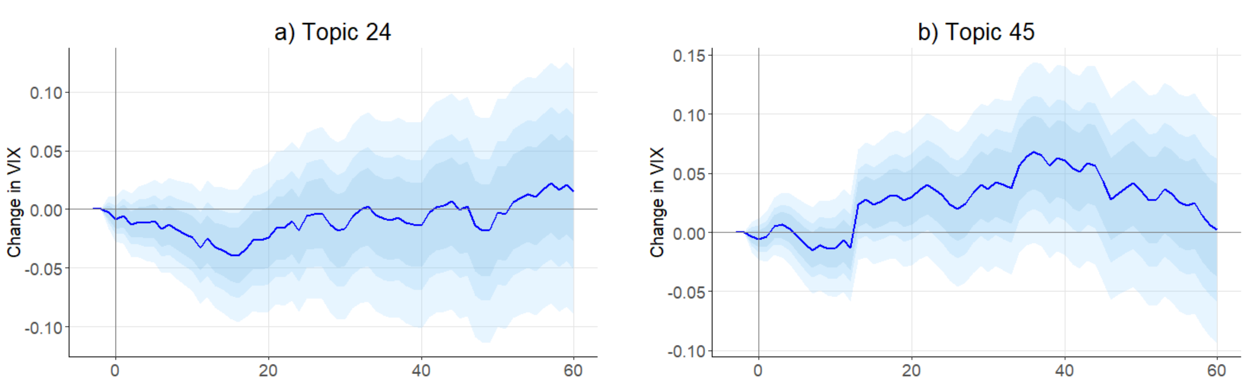
Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

Figure B.3: Responses of the change in the VIX to constituents of monetary policy metatopic



Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

Figure B.4: Responses of the change in the VIX to constituents of fiscal policy

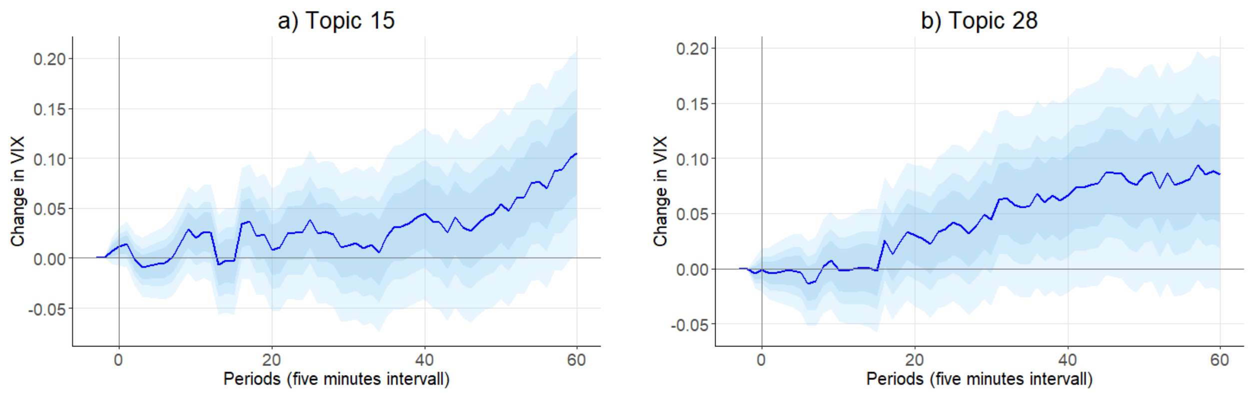


Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

C Impact of selected events on economic policy uncertainty

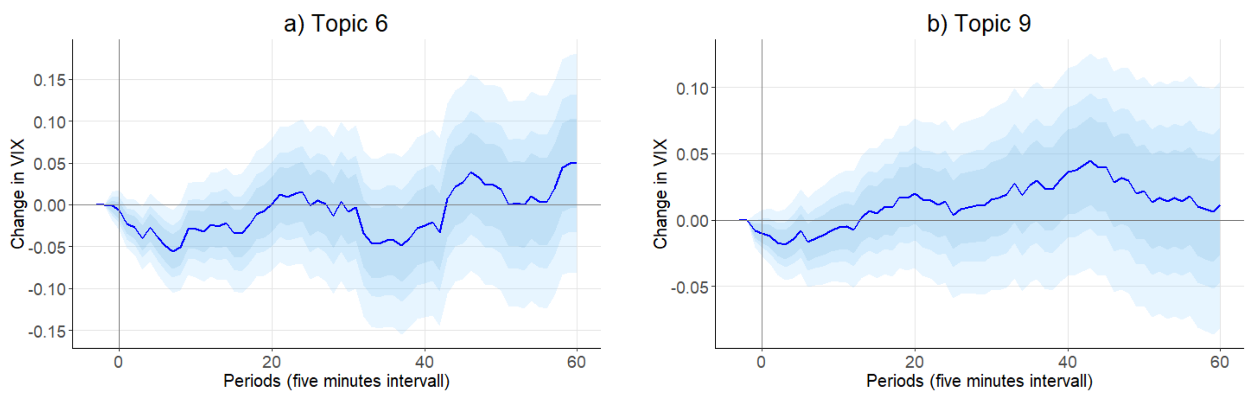
While the change in uncertainty in the main results section was short-lived and driven uniquely by actions taking by stock market participants, the change in uncertainty in this section is driven by the perception of 10 U.S. national coverage newspapers, and it is expected to last longer. The change in media perspective regarding the contribution of President Trump's announcements to overall economic policy uncertainty is not an economic outcome by itself, but a trigger for fluctuations in the real economy, as documented in Baker et al. (2016). The results in this section are based on estimated coefficients from Equation 5, with Δy_{t+h}

Figure B.5: Responses of the change in the VIX to constituents of immigration policy



Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

Figure B.6: Responses of the change in the VIX to constituents of health care



Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

defined as $\log{(EPU_h/EPU_l)}$, so it can be interpreted as the percentage point (pp) change in the EPU index from l days before the event to h days afterwards. Independent variables are defined as in section 3 for the behavior, single-topic, and meta-topic events. The following results are intended merely as an exploratory exercise since they are susceptible to identification problems and seasonal effects in the composition of the EPU series.

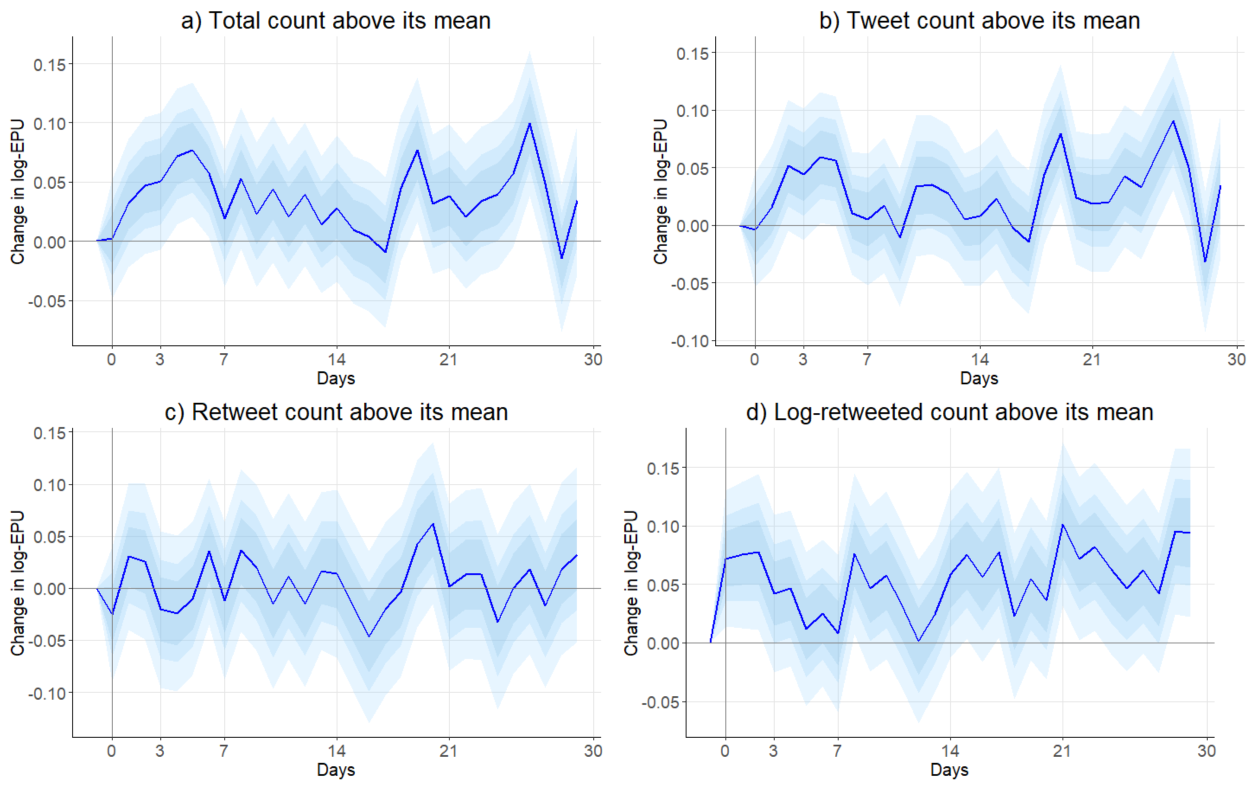
C.1 Impact of behavior events on economic policy uncertainty

Figure C.1 shows the estimated impulse responses to behavior events for each count variable above its mean. The first event is *total count above its mean*, which targets 576 days out of 1413 with more than 11 posts per day. The response for this event is significant at the 10% level for the period between 4 and 6 days after its occurrence, and also between 19 and 26 days. It achieves its highest value equal to 0.099 pp. after 25 days. Panel b) and c) in Figure C.1 suggest that the effect observed in the total count is mainly driven by tweets rather than retweets, which is not significant at any period. The behavior of Trump's followers is also relevant to policy uncertainty. Panel d) in Figure C.1 shows a significant immediate response in the EPU index when the number of retweets of Trump's posts exceeds the 18500 times mark.

Similar to results in section 4.1 one can observe a progression in the magnitude in the response to behavior events, as they become less likely to occur. For the case of tweet counts, as the condition threshold increases from *"tweet count above its mean"* in Figure C.1 panel b) to *"tweet count above* 60^{th} *percentile"* in Figure C.2 panel a), and *"tweet count above* 70^{th} *percentile"* in Figure C.2 panel b), the number of events reduces from 651 to 552, and 401 events accordingly. This progression effect translates in a 86% increase in response's magnitude, at the peaks at day four, form the first to the last panel mentioned above.

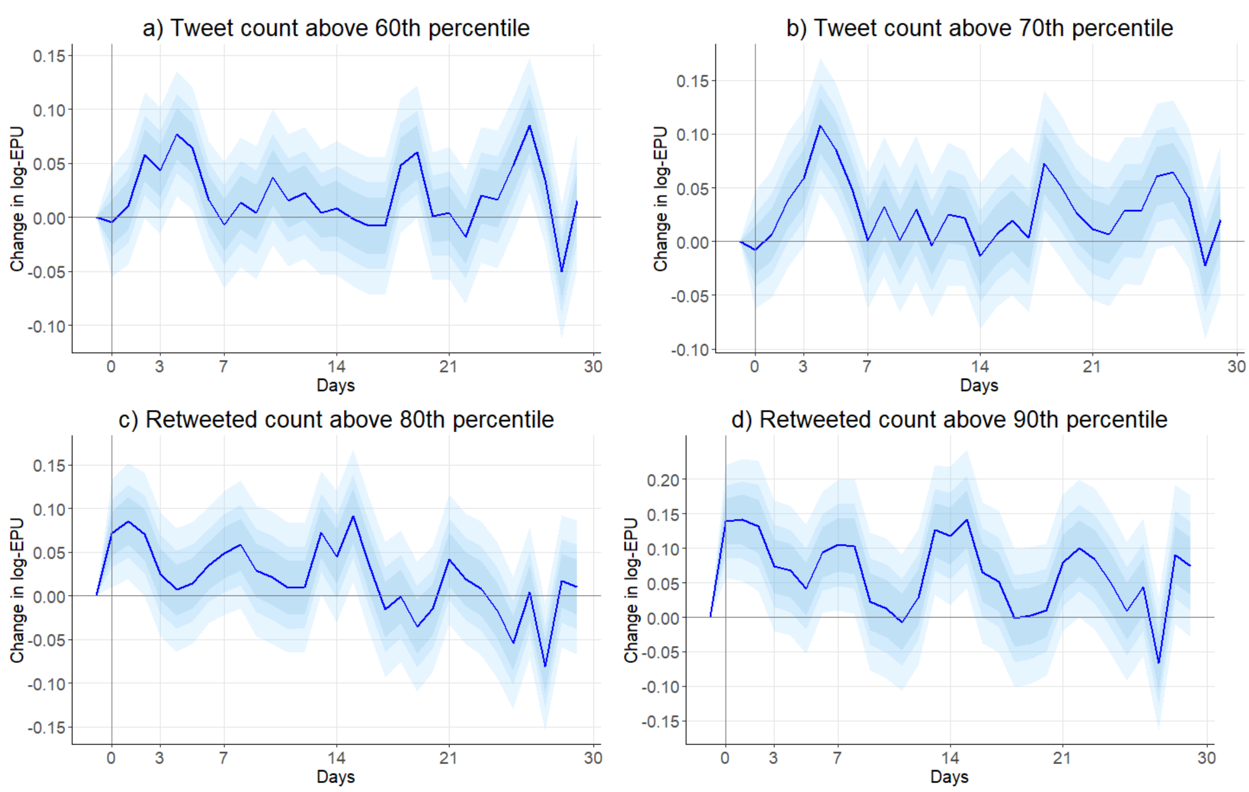
After comparing the estimated response for retweeted counts in Figure C.1 panel d) with the responses to similar events using 80^{th} and 90^{th} percentiles as thresholds (Figure C.2 panel c) and d), one can observe an increase in magnitude in the initial response, from 0.075 pp one day after the event in Figure C.1 panel d) to 0.14 pp in Figure C.2 panel d). Responses at periods 8, 13, 15, and 22 remain significant in all plots, but responses increase in magnitude as the threshold increases. These results may support the narrative that Trump's tweet behavior, including follower's behavior, may affect not only financial markets but a broad spectrum of economic activities that rely on certainty about future economic policies.

Figure C.1: Responses of change in the EPU index to behavior events



Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

Figure C.2: Responses of change in the EPU index to behavior events



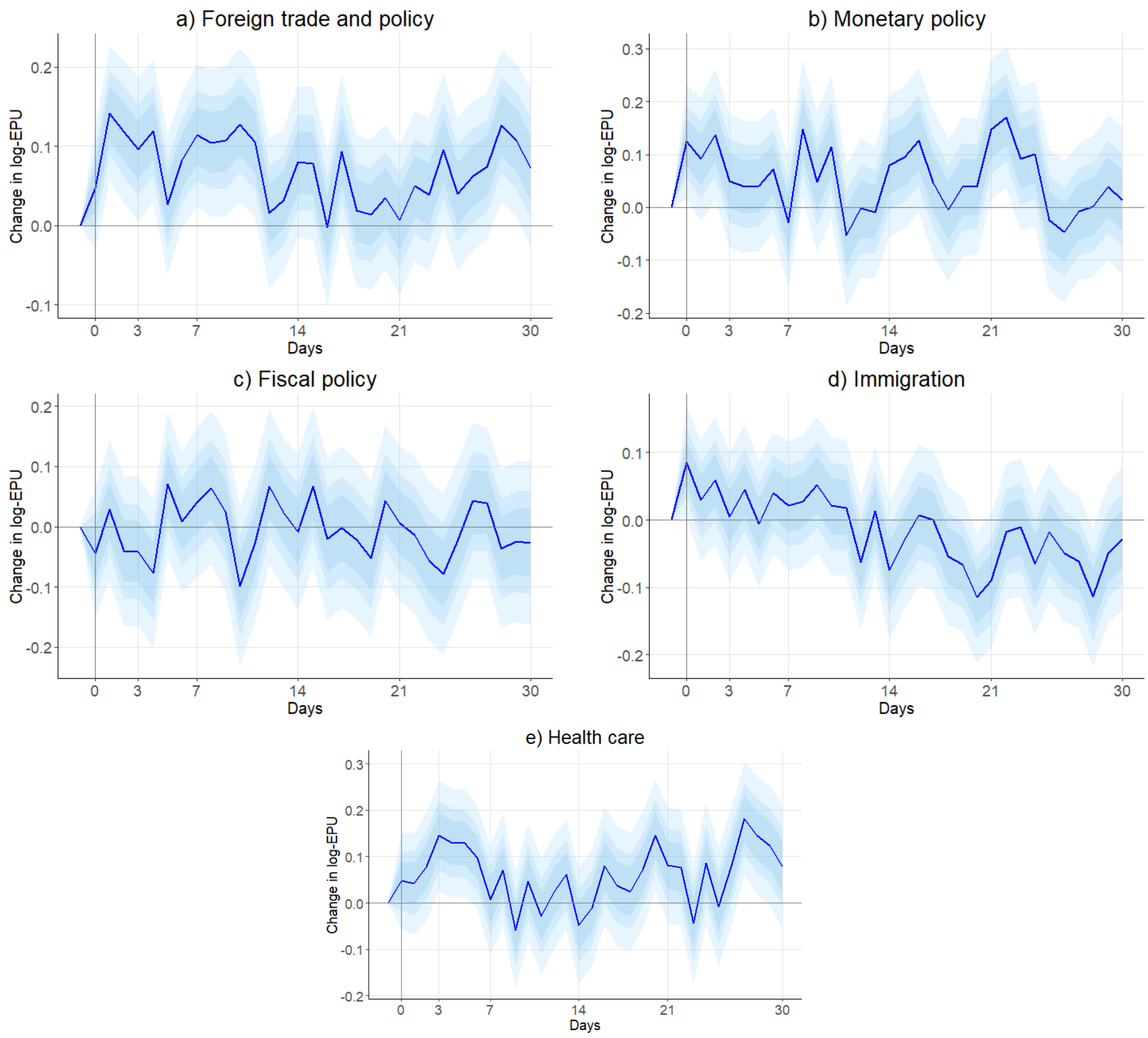
Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors.

C.2 Impact of behavior events on economic policy uncertainty

The second set of results in this section is based on meta-topics events defined as in 3 but aggregating tweets at the day level, such that the overall number of topics reduces relative to the five-minute sample but the coherence of the resulting topics increases (see average meta-topic coherence in table 3). One can attribute the gain in coherence to a larger corpus dealing with less variation in the vocabulary (see table). I estimate the responses of the change in the log-EPU Index $\Delta epu_{t,h}$ to these meta-topic events using Equation 5, allowing again for more than one meta-topic event happening at the same time but excluding behavior events and controls.

The meta-topic event *"foreign policy and trade"* in Figure C.2 panel a) presents a cumulative effect of 0.11 pp on average over the intervals 1 to 4, 7 to 11, and 28 to 29, where this effect is significant at the 10%

Figure C.3: Responses of change in the EPU index to meta-topic events



Note: This figure plots the estimated coefficients β_h in Equation 5 against h. Blue shaded areas represent confidence bands at the 5^{th} to 95^{th} percentile range, the 15^{th} to 85^{th} percentile range, and the interquartile range based on robust standard errors. Sample period 31.12.2015 23:11 CST to 21.10.2019 12:31 CST.

level. The maximal response of 0.14 pp increase in policy uncertainty appears after one day. The meta-topic event *monetary policy*, panel b), displays a similar fast reaction, with 0.12 pp (p-value equal to 0.051) for the contemporaneous effect. There are subsequent large and significant (at the 10% level) responses for this event after 2, 8, 21, and 22 periods, being this last period the largest response with 0.17% pp ($p - value = 0.03$). The effect of the *fiscal policy* meta-topic event, in panel c), is not significantly different from 0 over the whole horizon. These results put together are in line with the results from section 4.2, meaning that narratives regarding trade, foreign policy, and monetary policy spread relatively faster to the general public, later they are captured by the newspapers, which formally adds the "uncertainty" label on them.

The estimated responses for the effect of *immigration* and *health-care* events C.2, panels d) and e) contrast with the results observed for the VIX. The *immigration* meta-topic event displays an overall negative effect, with 0.084 pp contemporaneously, and about -0.11 pp after 20, and 28 days, all three coefficients significant at the 10% level. *Health care* is positive and significant in the period between 3 and 5 days (0.13 pp on average), 20 days (0.146 pp), 27 days (0.18 pp), and 28 days (0.14pp) after the event.

These results seem contradictory to the association of narratives regarding immigration policy changes with high uncertainty for foreign employees and national employers. However, newspapers used as sources for the EPU Index may have a different perspective when adding the label uncertainty to news regarding policy issues. One example of this is the news coverage of the open letter signed by 58 CEOs, stating the probable adverse consequences of Trump's immigration policy. Newspapers highlighted the counterproductive labor market effects without adding the keyword "uncertainty" [19] to the news body. *Health care* meta-topic events exhibit the expected sign, since it is a primary concern for a broad share of the American population, and narratives concerning Trump's disdain for "Obamacare" were massively covered by the media.

[19]This is a major drawback of word-based indices, the omission of a pre-defined word in an article, such as "uncertainty" exclude it from the index, even though it qualifies for it

C.3 Interaction between meta-topics and behavior events

Table C.1 summarizes previous results at five different time horizons, controlling for the number of posts and allowing for interactions between meta-topic events and behavior events of the form "*retweeted count above* 90^{th} *percentile*". The main effect of the meta-topic event "*foreign policy and trade*" remains significant and close in magnitude to the effect reported in Figure C.1, after adding control and interaction terms, within the first week. The interaction terms for this type of event is significant only after the third week, meaning that the increase in policy uncertainty at this horizon is driven by a heavily retweeted subset of tweets implying the trade and foreign policy narrative. The main effect of the meta-topic event *monetary policy* is significant only in the third week, but its interaction effect is more than four times larger in magnitude and significant in the third week and after a month. The main effects for *fiscal* and *immigration policy* are not statistically significant over the estimation horizon. The interactions are negative and significant after a month for *fiscal policy* and three weeks for *immigration*. The negative sign in fiscal policy was expected, but it did not appear to be significant in previous results. Nevertheless, The interaction term allows picking a depurated set of tweets regarding fiscal policy linked to periods with low policy uncertainty values. Finally, the main effect of the *health care* meta-topic event is positive and significant after three days and its interaction after a month.

Table C.1: Cumulative effect of main counts and economic related meta-topic events on change in the EPU index

	1 day		3 days		1 week		3 weeks		1 month	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	-0.031	-0.047	-0.058^{*}	-0.059^{*}	-0.005	-0.014	-0.024	-0.037	-0.060^{*}	-0.067^{*}
	(0.029)	(0.030)	(0.031)	(0.032)	(0.031)	(0.032)	(0.032)	(0.033)	(0.034)	(0.035)
Total count	0.0003	0.001	0.004^{*}	0.004^{*}	-0.001	-0.001	0.002	0.003	0.006^{**}	0.006^{**}
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Foreign policy and trade	0.141^{***}	0.119^{**}	0.093^{*}	0.065	0.115^{**}	0.121^{**}	0.006	-0.018	0.069	0.056
	(0.051)	(0.054)	(0.055)	(0.058)	(0.055)	(0.058)	(0.057)	(0.060)	(0.061)	(0.063)
Monetary policy	0.091	0.079	0.051	0.019	-0.028	-0.055	0.147^{*}	0.092	0.013	-0.034
	(0.071)	(0.074)	(0.076)	(0.080)	(0.076)	(0.080)	(0.080)	(0.084)	(0.085)	(0.089)
Fiscal policy	0.028	0.062	-0.037	-0.023	0.039	0.033	0.008	0.028	-0.022	0.029
	(0.070)	(0.073)	(0.075)	(0.079)	(0.075)	(0.079)	(0.078)	(0.082)	(0.083)	(0.087)
Immigration	0.029	0.004	0.004	-0.049	0.022	0.009	-0.091	-0.055	-0.031	-0.012
	(0.054)	(0.060)	(0.058)	(0.065)	(0.058)	(0.065)	(0.061)	(0.067)	(0.065)	(0.072)
Health care	0.042	0.037	0.142^{**}	0.138^{*}	0.008	0.006	0.080	0.090	0.074	0.019
	(0.067)	(0.070)	(0.072)	(0.076)	(0.072)	(0.076)	(0.076)	(0.080)	(0.081)	(0.085)
Retweeted $> 90^{th}p.$		0.157^{**}		0.004		0.079		0.114		0.050
		(0.069)		(0.074)		(0.074)		(0.077)		(0.082)
Foreign policy and trade × Retweeted $> 90^{th}p.$		0.254		0.315		-0.038		0.340^{*}		0.222
		(0.182)		(0.195)		(0.196)		(0.203)		(0.215)
Monetary policy × Retweeted $> 90^{th}p.$		0.196		0.391		0.297		0.670^{**}		0.585^{**}
		(0.249)		(0.267)		(0.268)		(0.278)		(0.294)
Fiscal policy × Retweeted $> 90^{th}p.$		-0.354		-0.098		0.073		-0.254		-0.587^{**}
		(0.250)		(0.268)		(0.269)		(0.278)		(0.295)
Immigration × Retweeted $> 90^{th}p.$		-0.024		0.190		0.005		-0.331^{**}		-0.208
		(0.144)		(0.155)		(0.155)		(0.161)		(0.170)
Health care × Retweeted $> 90^{th}p.$		0.078		0.086		0.016		-0.042		0.557^{**}
		(0.222)		(0.239)		(0.239)		(0.248)		(0.263)
Observations	1,411	1,411	1,409	1,409	1,405	1,405	1,391	1,391	1,382	1,382
Adjusted R^2	0.003	0.009	0.003	0.005	-0.001	-0.002	0.001	0.007	0.001	0.006

Note: Estimated coefficients β and γ coefficients in Equation 6 using daily frequency data for the EPU. Robust standard errors are shown in parenthesis. Significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Sample period 31.12.2015 23:11 CST to 21.10.2019 12:31 CST. Percentile 60^{th} is used for interaction terms in regression (3). Percentile 80^{th} is used for interaction terms in regressions (7) and (10).

Results from this section reinforce the close relationship between media coverage, economic narratives, and policy uncertainty. Media coverage may boost the transmission of the original policy narrative. Media bias can mutate the original message, amplifying or dampening its economic effect. Finally, media interest to present new stories may create new narratives from the original one. These processes may take time and be subject to editorial criteria, such as weekly or monthly analysis of current news, explaining the irregularities in the estimated responses observed in this section.