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## Uncertainty about Federal Reserve policy and Its transmission to emerging economies: Evidence from Twitter

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## **ADB Working Paper Series**

### **Uncertainty about Federal Reserve Policy and Its Transmission to Emerging Economies: Evidence from Twitter**

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**Abstract**

It is well known that a tightening or easing of the United States' monetary policy affects financial markets in emerging economies. This paper argues that uncertainty about future monetary policy is a separate transmission channel. We focus on the taper tantrum episode in 2013, a period with an elevated uncertainty about monetary policy, and use a data set that contains 90,000 Twitter messages ("tweets") on Federal Reserve tapering. Based on this data set, we construct a new index about monetary policy uncertainty using a list of uncertainty keywords. An advantage of this index is that it reflects uncertainty about a specific policy decision. An estimated vector autoregression (VAR) shows that uncertainty shocks lead to a fall in asset prices and a depreciation of local currencies. We also discuss the policy implications of this uncertainty channel of monetary policy transmission.

**JEL Classification:** E32, E44, E52

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# 1. INTRODUCTION

Tightening and easing policy steps of the United States' (US) Federal Reserve (Fed) are known to affect emerging market economies through various channels. Typically, a Fed tightening leads to a withdrawal of capital from emerging economies, a drop in asset prices, and a real depreciation of local currencies. These spillover effects are often the subject of major concerns of policymakers in emerging market economies. After the 2007–2009 global financial crisis, monetary policy steps have led to particularly strong spillover effects. The various rounds of Quantitative Easing (QE1, QE2, QE3), the subsequent exit from QE3 (“tapering”) and the eventual lift-off of the Federal Funds rate from the zero lower bound in December 2015 have led to sharp adjustments in emerging markets. Announcements of further monetary easing led to massive capital inflows into emerging economies. The eventual unwinding of asset purchases and the prospect of a lift-off reversed these flows—with all the painful consequences.

These spillovers originate from specific monetary policy decisions. Over the years since the global financial crisis, a second type of spillovers has emerged: spillovers stemming from the uncertainty about future monetary policy. Uncertainty spillovers exist above and beyond those stemming from specific policy steps. It is the uncertainty about the likely course of monetary policy that led investors to adjust their portfolios, thus leading to side effects on emerging markets. This uncertainty channel of international policy transmission has been highlighted by the financial press. *The Financial Times* not only recently titled the above-mentioned statement, but also stated that “Emerging markets call on Fed to lift rates and end uncertainty” (9 September 2015) and “Fed clarity on rates is the catalyst that uncertain markets need” (12 October 2015).

In this paper we quantify uncertainty spillovers, with a special focus on Asia, based on a novel data set. We focus on the “taper tantrum” episode in 2013, which was triggered by Fed chairman Ben Bernanke’s testimony on 22 May 2013. When he reflected about the possibility of exiting Quantitative Easing (QE) and starting the gradual normalization of monetary policy, markets reacted with high uncertainty, a rise in volatility, and a sharp increase in US bond yields. It is the strong market reaction that gave this period its name the “tantrum” episode. These spillover effects during the taper tantrum were particularly severe for emerging market economies, which experienced strong depreciation of domestic currencies and a sudden tightening of monetary conditions.

The taper tantrum period is resembling the recent debate about the first increase of the Federal Funds rate target after 9 years of near-zero policy rates: the tapering decision was expected for the June or July Federal Open Market Committee (FOMC) meeting, then for September 2013, and had finally been delayed to early 2014. Both the timing and the delays are similar to the “lift off” in 2015, causing observers to refer to a reappearance of the taper tantrum.

There is some quantitative evidence on tapering spillovers. The literature includes Eichengreen and Gupta (2013); Aizenman, Binici, and Hutchison (2014); Rai and Suchanek (2014); Sahay et al. (2014); Mishra et al. (2014); and Lim, Mohapatra, and Stocker (2014). These papers assess the magnitude of spillovers and the importance of domestic macroeconomic fundamentals for the sensitivity to tapering-related spillovers. They do not, however, shed light on the uncertainty channel of international policy transmission.

The key contribution of this paper is a novel data set: our data set consists of 90,000 Twitter messages (“tweets”), which reflect the entire discussion on the Fed tapering between April and October 2013 on Twitter.com. From this we construct an indicator of uncertainty about future monetary policy, which we then feed into a standard vector autoregressive (VAR) model. We use a comprehensive word list from the literature that contains keywords that describe uncertainty and apply this to all our tweets. This gives us an index of uncertainty that is directed to a very specific monetary policy decision. This is an important advantage over uncertainty indicators used in the literature, e.g., Baker, Bloom, and Davis (2013), which often reflect a broad, unspecific notion of uncertainty.<sup>1</sup> A second advantage is that we measure uncertainty directly from messages sent, read, and forwarded by market participants. A third advantage is that this index is available on a daily frequency.<sup>2</sup>

We find that an increase of uncertainty about the timing of the exit from QE leads to significant effects on emerging market economies. Uncertainty leads to a fall in bond and stock prices, a depreciation of local currencies, and an increase in credit default swap (CDS) spreads. Several robustness checks such as controlling for the macroeconomic environment, the information coming from FOMC meetings, and the number of retweets confirm our findings. Thus, this paper provides evidence of an uncertainty channel of international monetary policy transmission.

The results highlight the need for clear and consistent communication of major policy decisions of central banks in advanced economies. Major policy turnarounds such as the exit from QE should be designed with special attention to the vulnerabilities of emerging economies. This is particularly relevant for, among others, the European Central Bank and the Bank of Japan, which will have to communicate the exit from unconventional monetary policy at some point in the future. Our results also suggest that maintaining strong macroeconomic fundamentals in emerging markets is best suited to withstand uncertainty spillovers.

The remaining parts of the paper are organized as follows. Section 2 introduces our data set and explains the construction of the new measure of uncertainty about US monetary policy. Section 3 explains the empirical model used to estimate the effects of uncertainty shocks. Section 4 discusses the details and the robustness of the findings. A perspective on policy implications in Section 5 and a concluding section complete the paper.

## 2. MEASURING POLICY UNCERTAINTY WITH TWITTER DATA

We use a sample that captures the 2013 taper tantrum episode and, hence, a period in which market uncertainty about future US monetary policy was high and volatile. It is also a period with a major shift in expectations about the future course of US monetary policy. To estimate the effects of uncertainty, we need data (i) that is available on a high frequency in order to reflect the high-speed transmission of information on financial markets, (ii) that reflects uncertainty of actual market participants, not of the overall economy, and (iii) that allow us to isolate the specific uncertainty about

<sup>1</sup> Istrefi and Piloju (2013) use the Baker, Bloom, and Davis (2013) index of policy uncertainty for the US, the United Kingdom, Germany, and the euro area to quantify the response of inflation expectations to a broadly defined notion of uncertainty.

<sup>2</sup> The same data is used in Meinusch and Tillmann (2015) and Tillmann (2015). None of these papers, however, is investigating the effects of policy uncertainty in the US on emerging markets' asset prices and financial conditions, respectively.

monetary policy from the uncertainty about other fields of economic policy. For the latter reason, the commonly used indicator of policy uncertainty from Baker, Bloom, and Davis (2013) cannot be used as it summarizes uncertainty on a wide range of policy areas.

The core contribution of this paper is a new data set that allows the researcher to extract a measure of market participants' uncertainty on a high frequency. Instead of measuring expectations by counting newspaper articles like in Baker, Bloom, and Davis (2013) or inferring investor uncertainty from financial products, we turn to social media. Due to its ubiquity and responsiveness, social media is a promising data source for all research questions for which uncertainty of market participants plays an important role.

We have a data set that includes the entire discussion about the taper tantrum episode on Twitter.com. Twitter is a social media network on which users can exchange short text messages (tweets) of a maximum 140 characters. Twitter is popular among financial market professionals and Fed watchers. Importantly, Twitter users can not only send messages to followers, but also forward tweets or comment on other messages. Thus, we have a data set at hand that fulfills the criteria outlined before.

To be specific, we have the entire Twitter volume on Fed tapering between 15 April and 30 October 2013. This is the period for which most of the market reactions could be observed. The sample period is relatively short, which is dictated by data availability, but not too short to estimate a parsimonious model. With this in mind, we use a model below that leaves sufficiently many degrees of freedom.

The raw data has been provided by Gnip.com, which is now part of Twitter.com. The data was delivered in 10-minute intervals formatted in JASON.<sup>3</sup> The data set includes 87,621 tweets from 27,276 users located in 136 economies and the exact time they were sent. We transform the data into a spreadsheet format and normalize the time of each message to New York time. We remove public holidays and weekends in the US from these series because there is no financial data available on these days. In addition, very few tweets in languages other than English had to be removed. Panel (a) in Figure 1 plots the series of tweets aggregated to a daily series. The horizontal axis gives the days in the sample period. We see that the number of tweets explodes at the September 2013 FOMC meeting, for which the tapering decision of the Fed had been expected. However, the Fed decided to postpone tapering to a subsequent meeting. The number of tweets systematically increases not only around the September FOMC meeting, but also around other FOMC meetings. For that reason we will present below an estimation specification in which we control for FOMC meeting days. The scaling of the graph understates the magnitude of fluctuations in the number of tweets, which vary strongly over time.

Based on these text messages we want to derive a quantitative measure of uncertainty. For this purpose, we resort to text mining and use a dictionary with keywords that signal uncertainty of the sender of a given Twitter message. This dictionary of words is taken from the widely cited paper of Loughran and McDonald (2011).<sup>4</sup> This word list is particularly useful for our purposes because it is relatively comprehensive and particularly calibrated to reflect uncertainty in financial communication. A dictionary approach is preferable in our context because Twitter

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<sup>3</sup> The data is proprietary such that the raw data cannot be made available.

<sup>4</sup> Thus, we create an indicator of uncertainty which is based on the wisdom of the crowd in financial markets. This is similar in spirit to the index created by Bachmann, Elstner, and Sims (2013) from firm surveys, although we measure a more specific form of investor uncertainty.



messages are typically highly pointed, often cynical statements with frequent use of market jargon. Other text mining tools such as topic modeling might have difficulties grasping the full notion of each message.

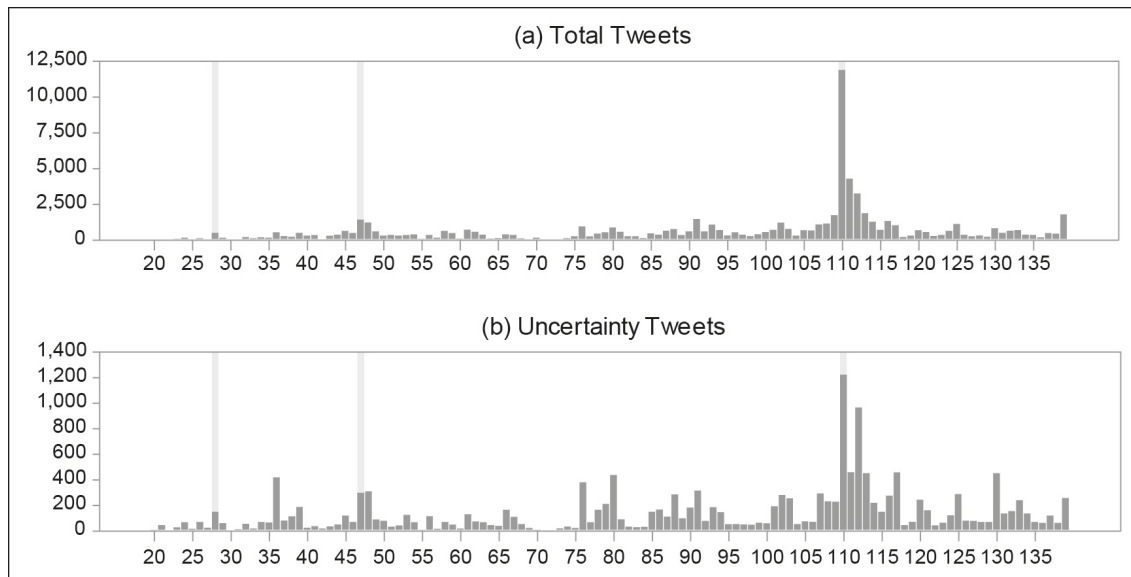
**Table 1: Uncertainty Keywords**

Abeance	Abeyances	Almost	Alteration	Alterations	Ambiguities
Ambiguity	Ambiguous	Anomalies	Anomalous	Anomalously	Anomaly
Anticipate	Anticipated	Anticipates	Anticipating	Anticipation	Anticipations
Apparent	Apparently	Appear	Appeared	Appearing	Appears
Appropriate	Approximated	Approximately	Approximates	Approximating	Approximation
Approximations	Arbitrarily	Arbitrariness	Arbitrary	Assume	Assumed
Assumes	Assuming	Assumption	Assumptions	Believe	Believed
Believes	Believing	Cautious	Cautiously	Cautiousness	Clarification
Clarifications	Conceivable	Conceivably	Conditional	Conditionally	Confuses
Confusing	Confusingly	Confusion	Contingencies	Contingency	Contingent
Contingently	Contingents	Could	Crossroad	Crossroads	Depend
Depended	Dependence	Dependencies	Dependency	Dependent	Depending
Depends	Destabilizing	Deviate	Deviated	Deviates	Deviating
Deviation	Deviations	Differ	Differed	Differing	Differs
Doubt	Doubted	Doubtful	Doubts	Exposure	Exposures
Fluctuate	Fluctuated	Fluctuates	Fluctuating	Fluctuation	Fluctuations
Hidden	Hinges	Imprecise	Imprecision	Imprecisions	Improbability
Improbable	Incompleteness	Indefinite	Indefinitely	Indefiniteness	Indeterminable
Indeterminate	Inexact	Inexactness	Instabilities	Instability	Intangible
Intangibles	Likelihood	May	Maybe	Might	Nearly
Nonassessable	Occasionally	Ordinarily	Pending	Perhaps	Possibilities
Possibility	Possible	Possibly	Precaution	Precautionary	Precautions
Predict	Predictability	Predicted	Predicting	Prediction	Predictions
Predictive	Predictor	Predictors	Predicts	Preliminarily	Preliminary
Presumably	Presume	Presumed	Presumes	Presuming	Presumption
Presumptions	Probabilistic	Probabilities	Probability	Probable	Probably
Random	Randomize	Randomized	Randomizes	Randomizing	Randomly
Randomness	Reassess	Reassessed	Reassesses	Reassessing	Reassessment
Reassessments	Recalculate	Recalculated	Recalculates	Recalculating	Recalculation
Recalculations	Reconsider	Reconsidered	Reconsidering	Reconsiders	Reexamination
Reexamine	Reexamining	Reinterpret	Reinterpretation	Reinterpretations	Reinterpreted
Reinterpreting	Reinterprets	Revise	Revised	Risk	Risked
Riskier	Riskiest	Riskiness	Risking	Risks	Risky
Roughly	Rumors	Seems	Seldom	Seldomly	Sometime
Sometimes	Somewhat	Somewhere	Speculate	Speculated	Speculates
Speculating	Speculation	Speculations	Speculative	Speculatively	Sporadic
Sporadically	Sudden	Suddenly	Suggest	Suggested	Suggesting
Suggests	Susceptibility	Tending	Tentative	Tentatively	Turbulence
Uncertain	Uncertainly	Uncertainties	Uncertainty	Unclear	Unconfirmed
Undecided	Undefined	Undesignated	Undetectable	Undeterminable	Undetermined
Undocumented	Unexpected	Unexpectedly	Unfamiliar	Unfamiliarity	Unforecasted
Unforeseen	Unguaranteed	Unhedged	Unidentifiable	Unidentified	Unknown
Unknowns	Unobservable	Unplanned	Unpredictability	Unpredictable	Unpredictably
Unpredicted	Unproved	Unproven	Unquantifiable	Unquantified	Unreconciled
Unseasonable	Unseasonably	Unsettled	Unspecific	Unspecified	Untested
Unusual	Unusually	Unwritten	Vagaries	Vague	Vaguely
Vagueness	Vaguenesses	Vaguer	Vaguest	Variability	Variable
Variables	Variably	Variance	Variances	Variant	Variants
Variation	Variations	Varied	Varies	Vary	Varying
Volatile	Volatilities	Volatility			

Source: Loughran and McDonald (2011). [http://www3.nd.edu/~mcdonald/Word\\_Lists.html](http://www3.nd.edu/~mcdonald/Word_Lists.html)

The word list is given in Table 1. We cover a broad range of words expressing uncertainty. Based on this dictionary we filter out all Twitter messages that contain at least one of these uncertainty words. These tweets are then aggregated to a daily series, which is depicted in panel (b) of Figure 1. This series is our indicator of market uncertainty about US policy. It can be seen that uncertainty is high on FOMC meeting days and also in the inter-meeting period. Comparing panel (a) and panel (b) of Figure 1 reveals that uncertainty is more evenly distributed over time than the raw data. This becomes evident after the September 2013 FOMC meeting (observation 110). While the overall number of tweets drops sharply after the meeting, the uncertainty measure does not, pointing to the fact that uncertainty about policy remained high even after the postponement of the tapering decision.

**Figure 1: Series of Twitter Messages**



Notes: Panel (a) reports the total number of tweets containing “Fed” and “taper” between 15 April and 30 October 2013. Panel (b) reports the number of uncertainty tweets on a given day as identified by the list of uncertainty keywords of Loughran and McDonald (2011).

Source: Prepared by author.

For the estimation stage below, we express the number of uncertainty tweets as a fraction of all tweets sent on the same day, i.e.,

$$Tweets_t^{uncertain} = \frac{\text{no. of uncertainty tweets on day } t}{\text{no. of all tweets on day } t}$$

An increase of this index is interpreted as a larger degree of uncertainty surrounding the Fed’s tapering decision. The denominator is reflecting the degree of attention the tapering debate receives on Twitter. We include this index in the VAR model in first difference, i.e.,  $\Delta Tweets_t^{uncertain}$ .

While each of our 90,000 tweets in isolation is not interesting and most likely contains a lot of noise, it is the large volume of messages that matters. We utilize the “wisdom of the crowds” to obtain a measure of policy uncertainty. A key advantage is that because all tweets, by definition, are about the tapering decision of the Fed, we know that the uncertainty reflected in the tweets is about the expected exit path from QE3.

Twitter users can not only send new messages, but also forward messages sent by others (“retweets”). We leave these retweets in the data set although they do not represent new information to Twitter users. The reason is that if a given message expresses uncertainty about policy and is forwarded often, the forwarding itself contains information about uncertainty that we do not want to ignore. In the results section, however, we will also present results for a specification in which we leave out retweets.

We now use the uncertainty measure derived in this section for an empirical examination of the transmission of uncertainty shocks to emerging economies.

### 3. THE EMPIRICAL MODEL

Since our aim is to model the effects of uncertainty shocks on emerging economies, we need to use a model that is able, first, to quantify the interaction among our measure of uncertainty, US real and financial conditions, and the financial conditions in emerging markets and, second, to identify the unexpected shock component of uncertainty. VAR models are typically used to accomplish these tasks. The VAR model we estimate has the following reduced form representation

$$Y_t = A_0 + A(L)Y_t + u_t, \quad E[u_t u_t'] = \Sigma_u,$$

where  $A(L)$  is a matrix polynomial in the lag operator of order  $p$  and  $u_t$  is a white noise process with variance-covariance matrix  $\Sigma_u$ . The constant of the VAR is  $A_0$ .  $Y_t$  is the vector of observable endogenous variables which includes the following variables at daily frequency

$$Y_t = (\Delta Tweets_t^{uncertain}, \Delta R_t^{US}, \Delta VIX_t^{US}, \Delta EM_t)'$$

For all variables  $\Delta$  denotes first differences, which were chosen to guarantee stationarity of the endogenous variables. The daily change in the number of uncertainty tweets relative to all tweets is  $\Delta Tweets_t^{uncertain}$ . Financial conditions in the US are approximated by the change in long-term bond yields,  $\Delta R_t^{US}$  (10-year constant maturity Treasury yields), and the change in the market volatility index (VIX) of implied stock market volatility,  $\Delta VIX_t^{US}$ . The first variable is included as it incorporated beliefs about future monetary policy, which we want to separate from the uncertainty about policy as such. The second variable is typically believed to reflect the product of investors' perceived risk and their degree of risk aversion. We need this variable below in order to identify uncertainty shocks.

$\Delta EM_t$  is the change in emerging markets' financial conditions. While the first three variables remain included in each estimation, the fourth variable is substituted by a range of series from emerging economies. We use one out of the following list of variables: the emerging market bond price index (EMBI) calculated and provided by J.P. Morgan, the emerging market stock price index (MSCI) stock price index for emerging markets, the nominal exchange rate of either Brazil, Indonesia, India, the Republic of Korea, Thailand, or Turkey, or the 12-month CDS spreads of Indonesia and Turkey. From these six emerging market economies, four (Brazil, Indonesia, India, and Turkey) belong to the group of the “fragile five” economies which were particularly hit by the taper tantrum. The Republic of Korea and Thailand, on the other hand, represent fundamentally more healthy economies. This will turn out to be important below when we compare the responses between relatively strong and relatively weak

economies. The exchange rate is defined such that an increase in the exchange rate is a devaluation of the local currency against the US dollar.<sup>5</sup> The VAR system is estimated with 10 lags.

The VAR model presented so far describes the reduced form dynamics of the four endogenous variables. To obtain a structural shock from the reduced form residuals  $u_t$ , identifying restrictions are needed. A common identification scheme is a Cholesky ordering, which imposes a certain order on the variables' responses on a given day. This is problematic if the focus is on the interaction between monetary and financial variables, for which we cannot a priori decide about the appropriate ordering. This is because policy uncertainty and the long-term interest rate are determined simultaneously. Therefore, in this paper we use Uhlig's (2005) sign restrictions on the impulse responses as an alternative. This procedure imposes restrictions on the signs of the responses and accepts only those draws that yield responses consistent with these constraints. Note that we only restrict the sign of some responses, but not their magnitude, significance, or persistence. Our main variable of interest, the change in emerging markets' financial conditions, is left unrestricted. The restrictions are imposed for 3 days and are summarized in Table 2.

**Table 2: Sign Restrictions to Identify an Uncertainty Shock**

$\Delta Tweets_t^{uncertain}$	$\Delta R_t^{US}$	$\Delta VIX_t^{US}$	$\Delta EM_t$
+		+	
(for t=0,2)	unrestricted	(for t=0,2)	unrestricted

Notes: For details see Uhlig (2005).

Source: Prepared by author.

An uncertainty shock is restricted to increase the number of uncertainty tweets and the change in the VIX on a given day. The restriction on the VIX is a common constraint in the literature on uncertainty shocks (Caldara et al. 2014; Caggione, Castelnovo, and Groshenny 2015). It is plausible to assume that an increase in uncertainty tweets also raises investors' risk aversion. It is important to note that we leave the response of emerging markets' variables unrestricted because we want to let the data speak. The response of the US bond yields, which we include as a control variable, will not be reported below. We expect that a shock that fulfills the constraints from Table 2 will lead to a drop in emerging markets' bond prices and a nominal depreciation of their local currencies. These responses would be in line with the anecdotal evidence from *The Financial Times* cited in the introduction.

In the discussion of the results we will not only present the impulse response calculated as the median of all draws, but also the single draw that gives a response that is closest to the median response (Fry and Pagan 2011). The reason is that the median of all draws leading to impulse responses could itself be not among the potentially observed responses. Therefore, we plot the median-target response as a robustness check.

## 4. RESULTS

In this section we present the results from the estimated VAR models. The effects of uncertainty shocks are highlighted in two stages. First, we illustrate the dynamic adjustment of the core variables, i.e., our uncertainty measure and the emerging markets variables, to an uncertainty shock. Second, we derive the contribution of the

<sup>5</sup> All data series are obtained from the Fred database of the Federal Reserve Bank of St. Louis.

uncertainty shock to the dynamics of each variable over time. This shed lights on the timing of uncertainty spillovers over the sample period.

## 4.1 The Responses to Uncertainty Shocks

Figures A1 to A.8 plot the responses of the most important variables to an uncertainty shock, that is, an unexpected increase in the degree of market participants' degree of uncertainty about future monetary policy. The impulse responses are surrounded by confidence bands reflecting the 16th and 84th percentiles of all draws. Since the US bond yield is included to control for aggregate market expectation of future police, we focus the discussion here on the responses of the uncertainty measure, the VIX index and, most importantly, the change in emerging markets' variables.

Figure A1 shows the response of the EMBI to an uncertainty shock. By construction, the relative share of uncertainty tweets increases and the VIX also increases. Since this has been imposed on the model, we will not further discuss these responses.<sup>6</sup> Instead, we will focus on the response of emerging markets to the uncertainty shocks. Our benchmark result is that an uncertainty shock leads to a drop of emerging markets' bond prices by around 0.3%. Both the median of all draws and the Fry–Pagan response indicate a fall in bond prices. The response is not very persistent beyond a horizon of 2 days, which is due to the fact that we include the variables in first differences.

Note that the shock we study here is a typical shock of one standard deviation. On many days in our sample, it is likely that the surprise movement in the uncertainty tweets is a multiple of one standard deviation. In this sense, the result in Figure A1 reflects the lower bound of the realized effects.

Figure A2 shows the response of the MSCI to an uncertainty shock. The magnitude of the response is similar to that of the EMBI, although the peak response is observed one period after the shock.

The different exchange rate series (Figures A3 to A8) show that, in general, an uncertainty shock leads to a depreciation of the national currency against the US dollar. A one standard deviation shock leads to a depreciation of about 0.4% in Brazil (Figure A3), Turkey (Figure A4), and India (Figure A5). Hence, uncertainty shocks appear to have sizeable effects on emerging financial markets. The only exception to this is Indonesia (Figure A6). Uncertainty shocks are found to have no effect on the rupiah. Interestingly, the effects of the uncertainty shock on the won and the baht are substantially smaller (Figures A7 and A8). A standard shock leads to a depreciation of the won by only 0.2%. This reflects the fundamental resilience of the Republic of Korea's economy to monetary spillovers. In 2013, the Republic of Korea and also Thailand were in a relatively better fundamental position compared with the other economies.

Finally, we also estimate the effect on CDS spreads of Indonesia and Turkey. These spreads are often interpreted as an insurance premium against a sovereign default. We found that CDS spreads increase for both countries, with the increase being twice as large in Indonesia (Figure A9) compared with Turkey (Figure A10). This is most likely again reflecting the fundamental weakness of Indonesia, which is even more aggravated than Turkey's macroeconomic vulnerability.

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<sup>6</sup> The full set of responses is available upon request.

## 4.2 The Contribution of Uncertainty Shocks

Of course it is not only interesting to see how a prototypical uncertainty shock affects emerging markets, but also to see ex post when such a shock has been particularly relevant. Although we use a relatively small sample period, we expect uncertainty shocks to be particularly relevant in the days leading up to FOMC meetings. For this purpose, we can use the information from the estimated VAR model and derive a historical decomposition, that is, to compare the baseline model with a model in which the uncertainty shock is switched off. The difference between both scenarios is informative about the contribution of the uncertainty shock to each variable's dynamics over time.

Figures A11 to A20 depict the observed variables we included in the estimated VAR model, as well as the part of the variable accounted for by the identified shock. The overall finding is that the uncertainty shock explains a sizable fraction of the fluctuations in emerging markets' variables. A surprisingly large portion is driven by uncertainty alone. Note that the shock we identify is not associated with a particular direction of the policy change.

Changes in the EMBI (Figure A11) are found to be well explained by uncertainty shocks. In particular, the EMBI movements between observation 70 and observation 100 of the sample are predominantly caused by the uncertainty shock. Furthermore, uncertainty explains the last 20 observations very well. This is remarkable because in its September 2013 meeting the Fed postponed the tapering decision. Our results show that after this meeting uncertainty spillovers became even more important.

The same observation can be made for the other variables. In each case the uncertainty shock is responsible for a large share of the dynamics over time. We also find that the bars reflecting the contribution of uncertainty shocks have the largest explanatory power after the June 2013 FOMC meeting, when the tapering decision was postponed and markets were left unsure about the subsequent policy path. The evolution of the MSCI (Figure A12) is also characterized by the very high explanatory power of the uncertainty shock at the very end of the sample period. The exchange rate series (Figures A13, A14, A15, A16, A17, and A18) all reveal that uncertainty spillovers were particularly pronounced at the very end of the sample period.

Uncertainty shocks also explain CDS spreads fairly well (Figures A19 and A20). This is particularly the case around the June 2013 FOMC meeting, when CDS spreads increased sharply due to tapering expectations.

## 4.3 Robustness

In this section we perform three alternative estimations in order to underline the robustness of the findings presented before. In particular, we allow for (i) dummies to capture the movements of uncertainty on important FOMC meeting days such as the September 2013 meeting, (ii) tweets being weighted by the number of followers of a particular Twitter user, and (iii) the macroeconomic environment affecting uncertainty.

### Including Policy Events

Before we showed that the model generates large contributions of uncertainty shocks to the observed variables on FOMC meeting days. One caveat is that on these days, Twitter users might simply distribute the information issued by the Federal Reserve. Put differently, we need to check whether the model shows responses to uncertainty in the intermeeting period, when there is no official Fed communication. It is this

intermeeting period where the discourse on Twitter should be particularly important for shaping market uncertainty. Figure A21 reports the impulse responses for the benchmark model, e.g., the model with the EMBI, in which we included dummies for the Bernanke testimony on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting. These are the three events that arguably had the largest impact on market uncertainty. Including dummies for other FOMC meetings in July and October does not change these findings. It can be seen that our benchmark results survive: the uncertainty shock leads to a drop in bond prices of 0.3%. Hence, the model performs equally well if we disregard days with official Fed communication that lead to a market-wide increase in uncertainty. Thus, our results are not due to the fact that Twitter users merely share the official FOMC after-meeting statements.

### Weighting Tweets by Number of Followers

Our data set includes every tweet on Fed tapering sent between April and October 2013. While many of these tweets were sent by users with thousands of followers such as institutional investors, journalists, and newswires, others came from users with hardly any followers such as private users. It could be argued that if a Tweet contains news, it is more effective the higher the number of followers. Note that even a tweet that is read by only a handful of people can be effective if it is retweeted often enough—since we do not know how often a given tweet has been forwarded, controlling for the number of followers is an acceptable approximation to the attention a tweet receives.

Figure A22 presents the benchmark specification in which we now weight each tweet with the number of followers of the sender's account. This is divided by all tweets sent on a particular day whereby each tweet is also weighted by the number of followers. We find that our basic result prevails: a shock to uncertainty leads to an outflow of capital from emerging economies and, as a consequence, a fall in emerging markets' bond prices. Note that the response can be observed for more than a week. A one-time shock leads to a persistent decline in bond prices. Hence, using unweighted tweets in our baseline specification is not too strong an assumption.

### Controlling for Macroeconomic Fundamentals

The degree of uncertainty about future policy depends on the macroeconomic situation. Signs of a strong recovery, say, would make an early tapering decision more likely and reduce the uncertainty about policy timing, respectively. Hence, controlling for business cycle data is a useful robustness check in order to find out whether our results are sensitive to the economic environment. A practical problem arises if one wants to include a measure of the business cycle: since we work with daily data, standard macroeconomic variables such as real gross domestic product (GDP) growth, unemployment, or inflation cannot be used as they are available on monthly or quarterly frequency only. Fortunately, Aruoba, Diebold, and Scotti (2009) offer an alternative: they constructed a daily measure of real economic activity in the US economy, which we can use for our purposes. We include their indicator in first differences,  $\Delta ADS_t^{US}$ , along with our baseline variables

$$Y_t = (\Delta ADS_t^{US}, \Delta Tweets_t^{uncertain}, \Delta R_t^{US}, \Delta VIX_t^{US}, \Delta EM_t)'.$$

The identification restrictions remain unchanged. Figure A23 depicts the resulting impulse responses following an uncertainty shock. Again, we report only the most important responses and leave out the response of the macroeconomic indicator.

We see that our baseline findings remain unchanged. An uncertainty shock leads again to a drop in asset prices. The EMBI falls by 0.2% on impact. Hence, controlling for the macroeconomic environment does not change our overall findings. That also means that the tweets in our sample do not simply reflect the interpretation of news releases such as non-farm payroll employment and inflation.

Taken together, we find robust evidence for an uncertainty channel of international policy transmission. The uncertainty about future policy itself has an effect on emerging markets' asset prices. This effect comes on top of the regular spillovers of policy changed in the US on emerging financial markets. The uncertainty channel gives rise to important policy implications, which are discussed in the following section.

## 5. POLICY IMPLICATIONS

The results presented in this paper underline two important policy implications, which are discussed in turn.

The first implication pertains to the design of monetary policy in advanced economies. Our results suggest a need for better communication of policy changes. In general, monetary policy should be as predictable and transparent as possible in order to allow markets to price in future policy movements. This is important from the perspective of the domestic economy, but also relevant from the perspective of emerging economies. The changing uncertainty studied in this paper has been the result of an ill-designed communication of a major policy turnaround. When Fed chairman Bernanke gave his testimony on 22 May 2013, he did mention the possibility of a reduction in bond purchases under QE3—an obvious consequence of a persistent economic recovery. Although his remarks were carefully crafted, markets nevertheless overreacted. While part of the overreaction might have been due to an irrational panic, the taper tantrum suggests that carefully communicating policy steps and, in particular, policy reversals, is crucial. This is an important lesson for central banks such as the Bank of England, the Bank of Japan, or the European Central Bank, for which the exit from unconventional measures and the return to policy normalization is yet to come. These central banks could learn from the taper tantrum case study about how to contain market jitters during the process of policy normalization.

The Fed itself has learned from the communication mistakes in 2013. The lift-off of the Federal Funds rate target by 0.25 percentage points in December 2015, although delayed several times like in 2013, has been very well anticipated by financial markets. This was the consequence of an improved communication strategy of the Federal Reserve. Markets reacted in advance of the actual interest rate rise, such that the eventual decision was received without an increase in volatility. The future path of interest rate normalization will again require clear and predictable policy communication. Whether the Fed will manage subsequent interest rate changes as well as the recent one remains to be seen. Some observers are skeptical: Bloomberg (20 November 2015) titles that [Federal Reserve Bank of St. Louis President James] “Bullard Says Investors Should Prepare for Uncertainty Era” and foresees that each FOMC meeting in 2016 will be “surrounded by elevated degrees of uncertainty.”

The elevated volatility at the beginning of 2016, i.e., after the first Fed interest rate hike, lends importance to a credibly policy strategy. Some argue that because of the rapidly changing global environment the first interest rate hike was a mistake and should be reversed. The Fed correctly responded to this by stressing how careful it will be as regards the timing of the next rate increase.



The second implication addresses macroeconomic policymaking in emerging economies. It is widely accepted that domestic macroeconomic weaknesses make emerging market economies more prone to policy spillovers from advanced economies. Recent work by Ahmed, Coulibaly, and Zlate (2015), Georgiadis (forthcoming), and others shows that the exposure to spillovers depends on domestic macroeconomic fundamentals, with the strength between fundamentals and spillovers varying strongly across economies and over time. Furthermore, the spillovers of Fed tapering received special attention. Eichengreen and Gupta (2013) and Aizenman, Binici, and Hutchison (2014) found that stronger fundamentals do not shield emerging economies from spillover effects, while the paper by Ahmed, Coulibaly, and Zlate (2015) argued that economies with stronger fundamentals are less affected by tapering shocks.

This line of research typically estimates whether a policy change in the US leads to asset price changes in emerging economies and whether this response is varying across economies together with macroeconomic fundamentals. Importantly, these papers focus on spillovers originating from tightening or easing steps, respectively, of the Federal Reserve—not from the uncertainty surrounding the future policy path.

A small amount of literature studies the role of fundamentals for the susceptibility of emerging economies to monetary policy uncertainty. Gauvin, McLoughlin, and Reinhardt (2014) provided evidence of general policy uncertainty in mature economies as a determinant of international capital flows to emerging economies. They used the policy uncertainty indicators of Baker, Bloom, and Davis (2013), but not a focused measure of specific monetary policy uncertainty such as the one used in this paper. They also showed that fundamentals play a role in determining the magnitude of spillover effects. Additional evidence is provided by Carrière-Swallow and Céspedes (2013). These authors showed that global uncertainty shocks, again measured by identifying episodes of exceptionally high realizations of the VIX index in the US economy, drive capital flows. Most importantly, domestic macroeconomic vulnerability increases the effects of uncertainty shocks on emerging economies.

Based on the results presented in this paper we can see that the exchange rate response is stronger in Brazil, India, Indonesia, and Turkey compared with the Republic of Korea and Thailand. While the former countries belong to what has been called the “fragile five” economies with particularly weak fundamentals, the Republic of Korea and Thailand had much stronger fundamentals. Hence, we find *prima facie* evidence that the sensitivity to uncertainty shocks does indeed vary according to domestic fundamentals, although a more systematic analysis is needed here to underline this finding.

Taken together, strengthening the resilience of emerging economies should reduce the sensitivity of policy spillovers and also uncertainty spillovers. A policy that tackles imbalances in government budgets and current account balances, avoids excessive indebtedness, and strengthens domestic financial institutions is best suited to cope with spillovers of any kind. In addition, macroprudential policy instruments are often seen as a promising toolkit for avoiding financial imbalances in the light of volatile capital inflows.

## 6. CONCLUSIONS

This paper provided evidence of an uncertainty channel of international monetary policy transmission. We showed that asset prices in emerging market economies responded to heightened uncertainty about future US monetary policy. The key contribution of this paper is the use of social media data from Twitter.com, from which an indicator of uncertainty is derived. An advantage of this data set is that we derive uncertainty directly from market participants' Twitter comments and that uncertainty focuses on a particular policy decision. Based on this data and an estimated VAR model we found that uncertainty affects emerging markets above and beyond the actual tightening and easing policy steps. Hence, mitigating uncertainty itself is beneficial from an emerging market's point of view.

Our results not only have implications for economic policymaking, as elaborated in Section 5, but also for future research on monetary policy in small open economies. Data from social media sources has not yet been widely used for understanding monetary policy. In many fields of monetary policy, expectations of market participants matter—whether it is about future policy or future inflation. In these cases, social media might be particularly useful as it allows researchers to measure market views directly from the relevant people and on a very high frequency.

Even after the Fed has exited unconventional monetary policies, many central banks such as the European Central Bank and the Bank of Japan are currently extending their unconventional set of policies. From the perspective of emerging market economies, in particular those in Asia, the time of strong policy spillovers is far from over. This paper provided some insights into the likely consequences of future policy uncertainty.

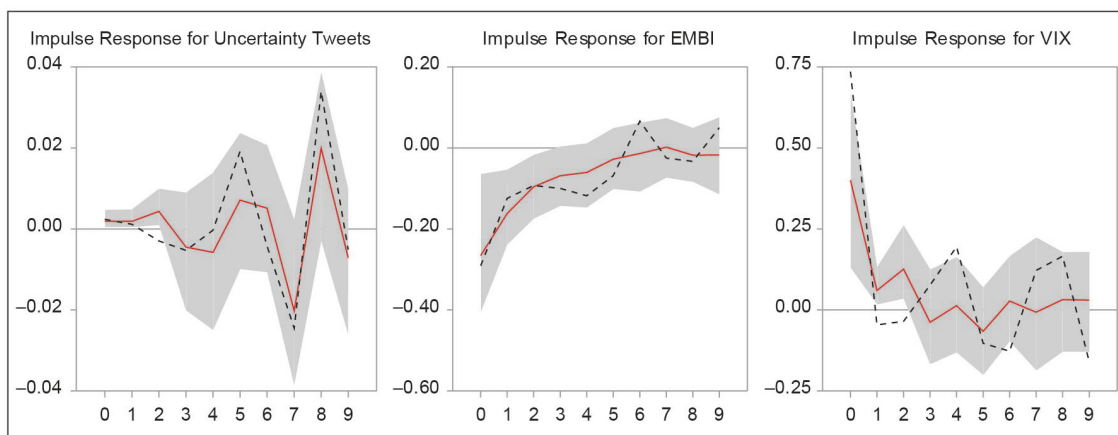
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## APPENDIX

**Figure A1: Response of EMBI to Uncertainty Shock**

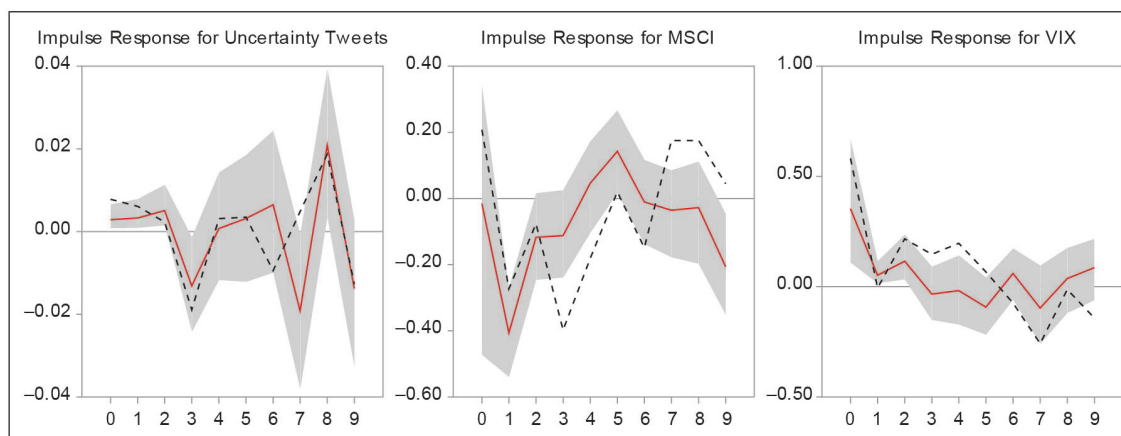


EMBI = emerging market bond price index; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A2: Response of MSCI to Uncertainty Shock**

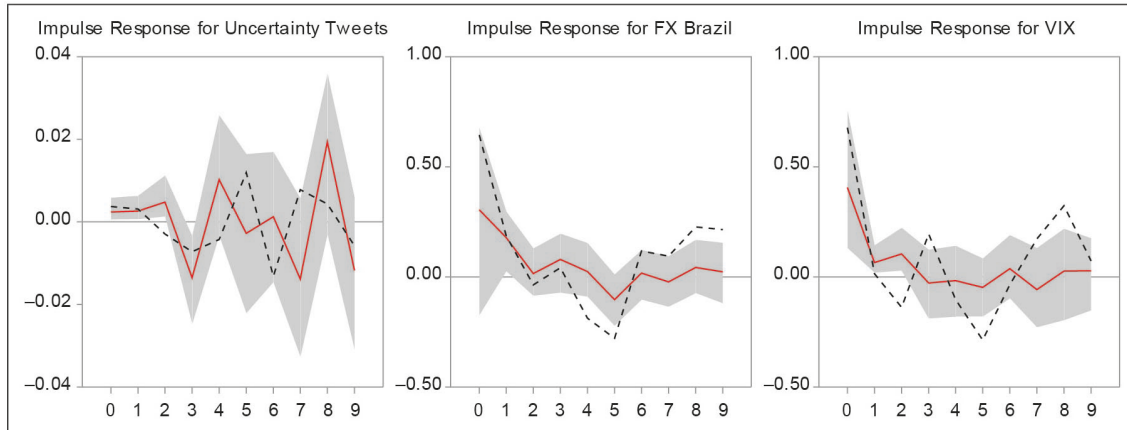


MSCI = emerging market stock price index; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A3: Response of FX Rate of Brazil to Uncertainty Shock**

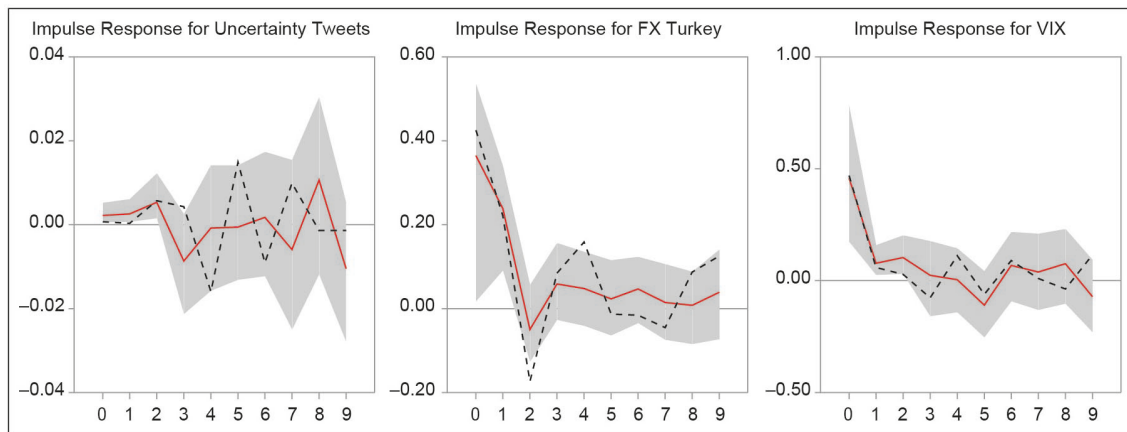


FX = foreign exchange; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A4: Response of FX Rate of Turkey to Uncertainty Shock**

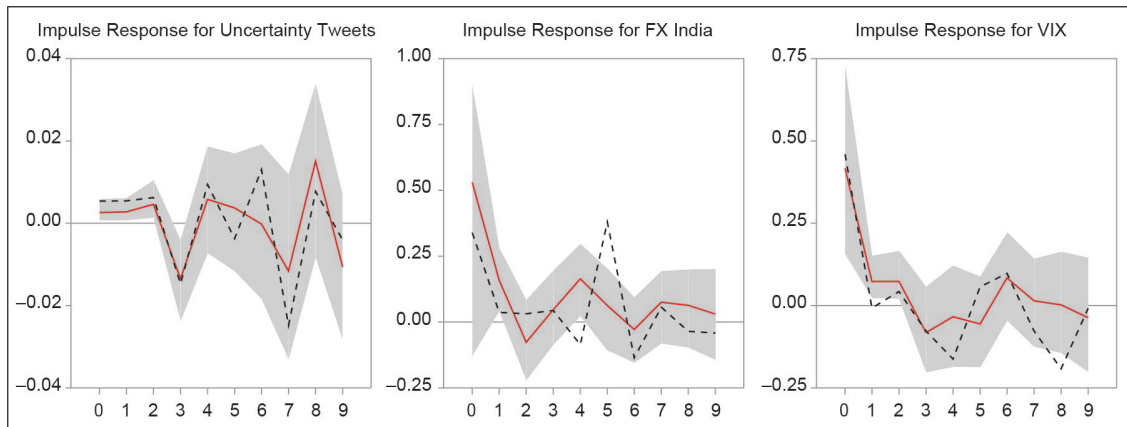


FX = foreign exchange; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A5: Response of FX Rate of India to Uncertainty Shock**

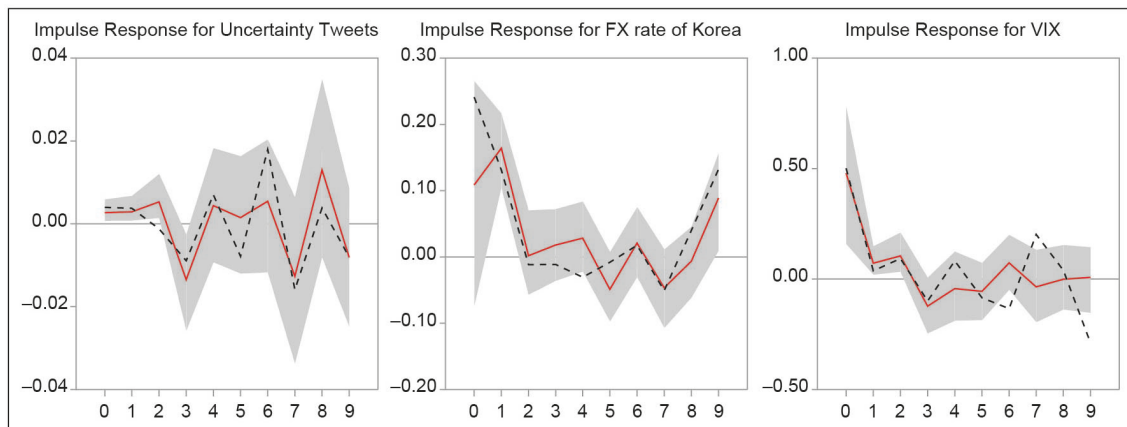


FX = foreign exchange; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A6: Response of FX Rate of Indonesia to Uncertainty Shock**

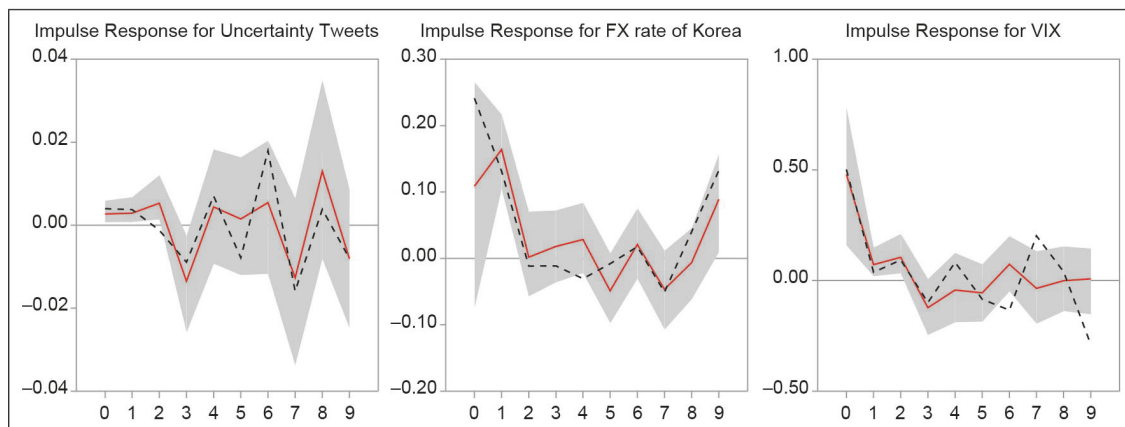


FX = foreign exchange; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A7: Response of FX Rate of the Republic of Korea to Uncertainty Shock**

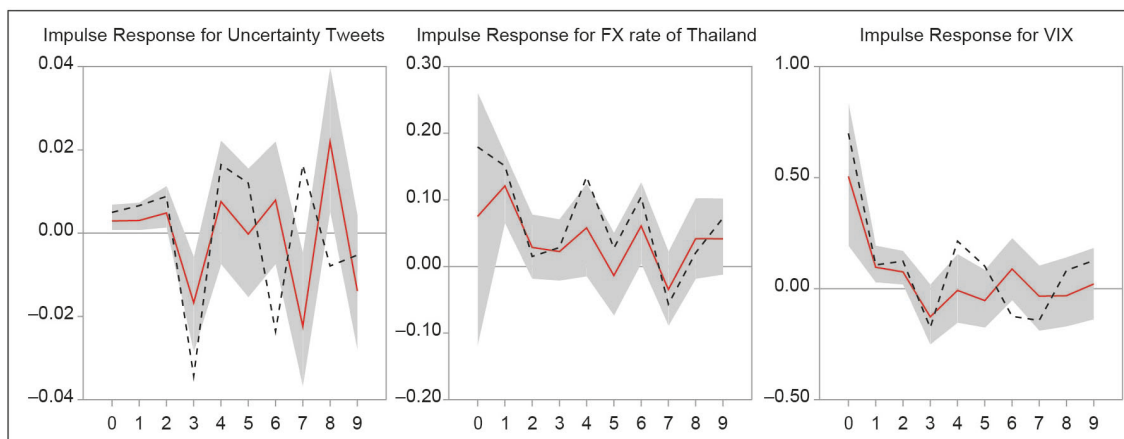


FX = foreign exchange; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A8: Response of FX Rate of Thailand to Uncertainty Shock**

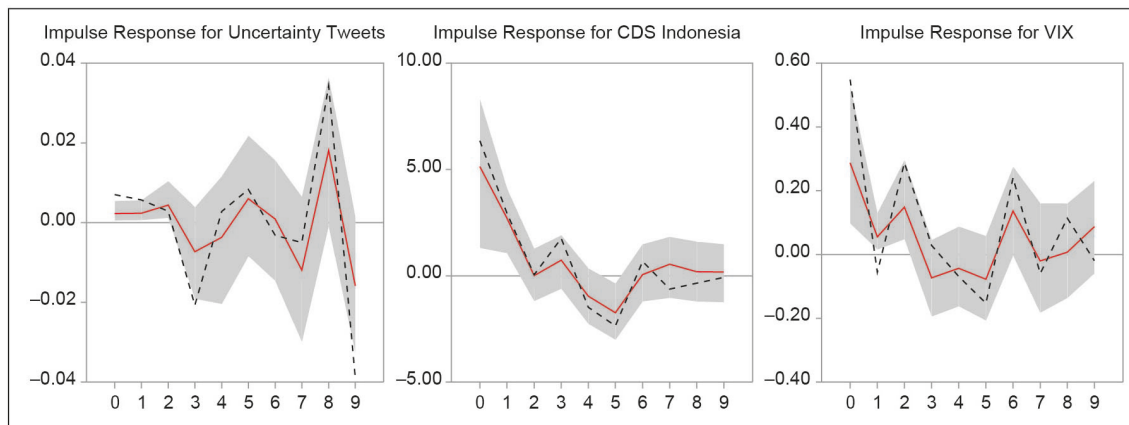


FX = foreign exchange; VIS = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

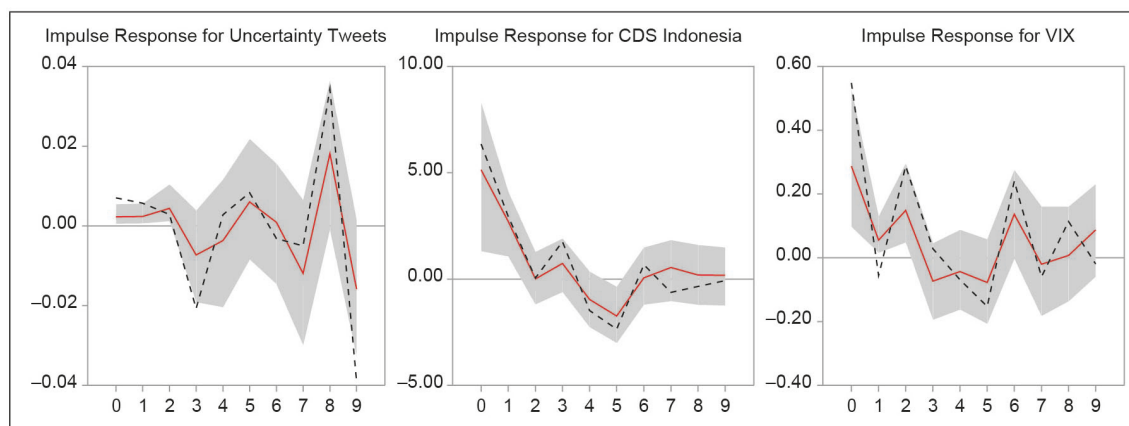


**Figure A9: Response of CDS Spreads of Indonesia to Uncertainty Shock**

CDS = credit default swap; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A10: Response of CDS Spreads of Turkey to Uncertainty Shock**

CDS = credit default swap; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

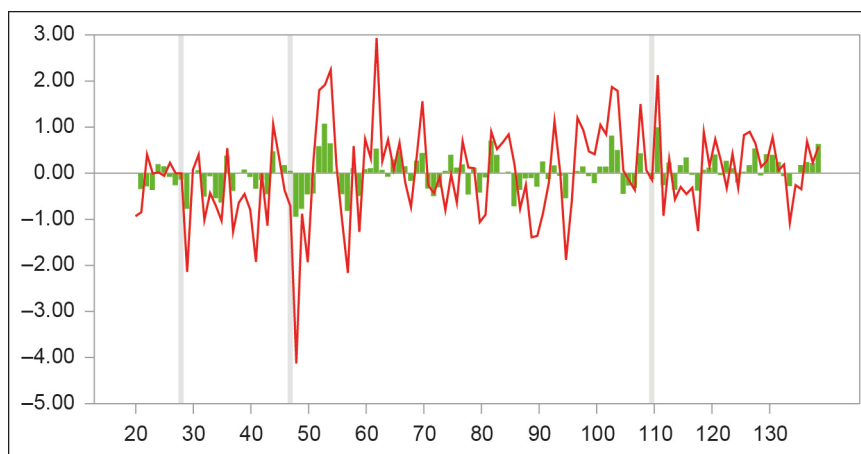
Source: Prepared by author.

**Figure A11: Contribution of Uncertainty Shock to EMBI**

EMBI = emerging market bond price index.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

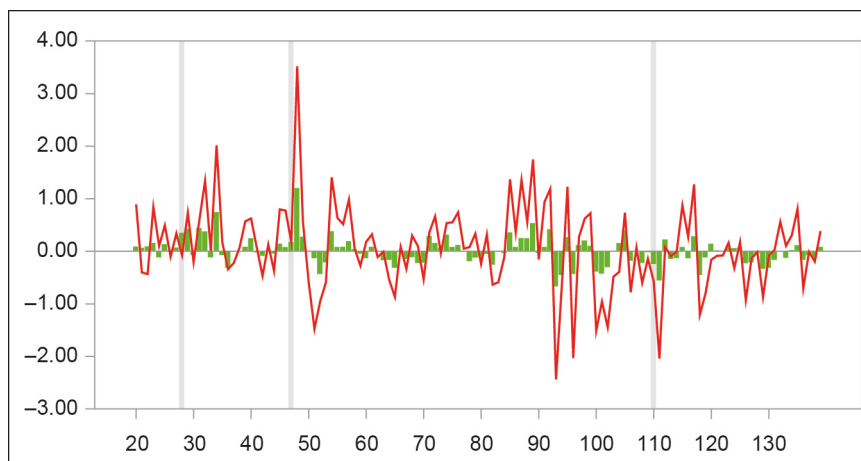
Source: Prepared by author.

**Figure A12: Contribution of Uncertainty Shock to MSCI**

MSCI = emerging market stock price index.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

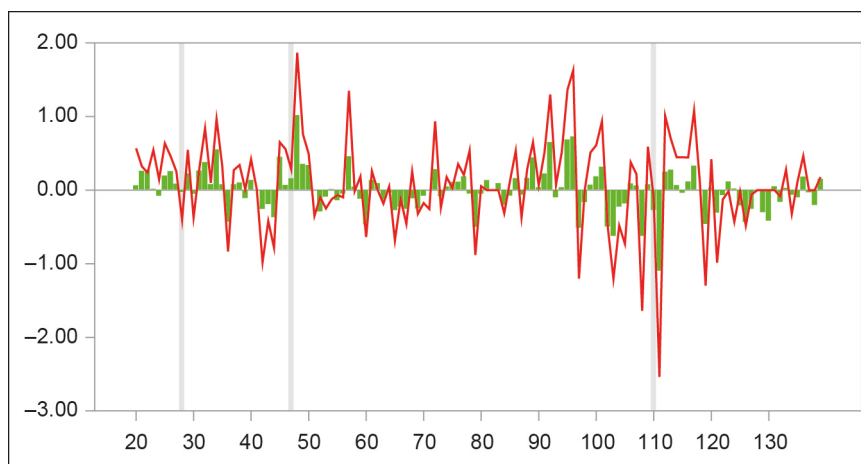
Source: Prepared by author.

**Figure A13: Contribution of Uncertainty Shock to FX Rate of Brazil**

FX = foreign exchange.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

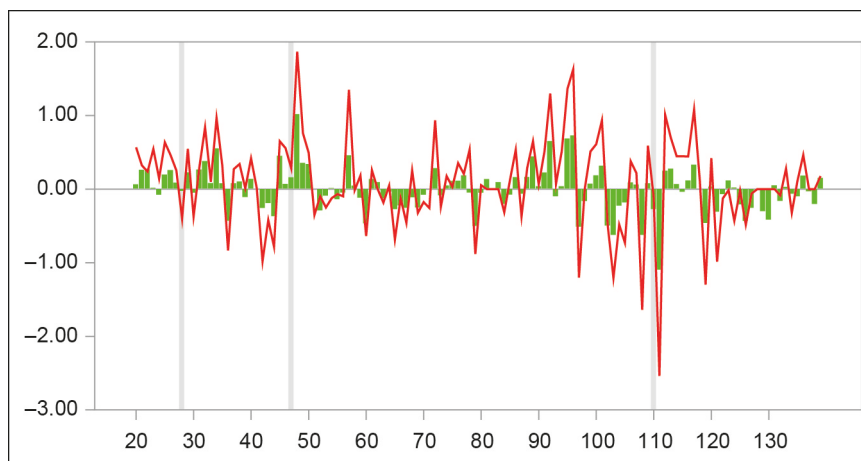
Source: Prepared by author.

**Figure A14: Contribution of Uncertainty Shock to FX Rate of Turkey**

FX = foreign exchange.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

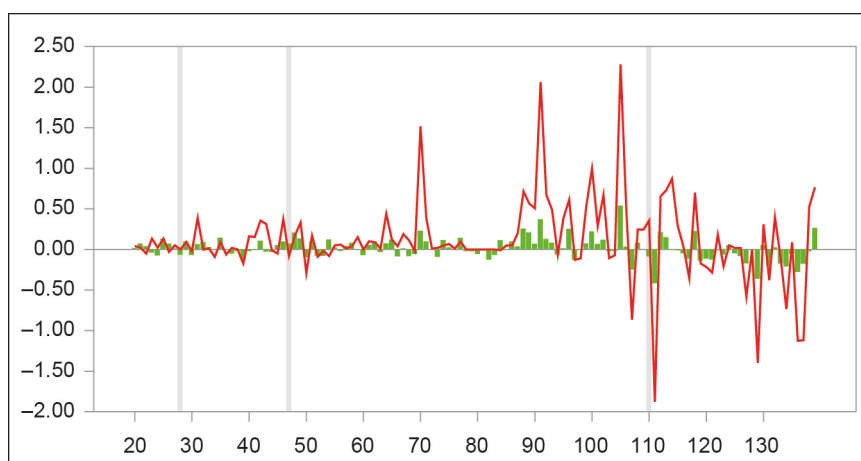
Source: Prepared by author.

**Figure A15: Contribution of Uncertainty Shock to FX Rate of India**

FX = foreign exchange.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

Source: Prepared by author.

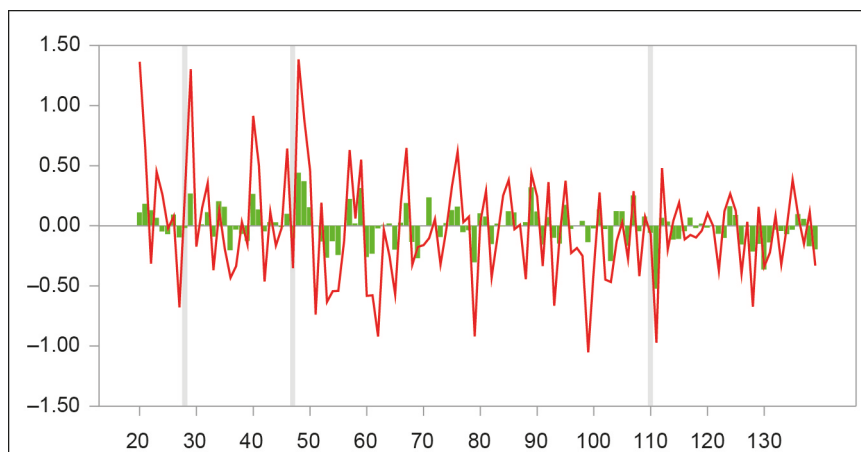
**Figure A16: Contribution of Uncertainty Shock to FX Rate of Indonesia**

FX = foreign exchange.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

Source: Prepared by author.

**Figure A17: Contribution of Uncertainty Shock to FX Rate of the Republic of Korea**

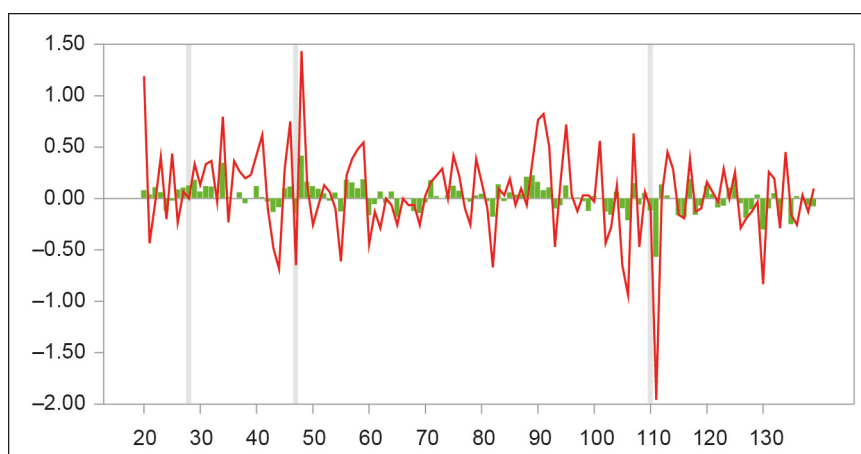


FX = foreign exchange.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

Source: Prepared by author.

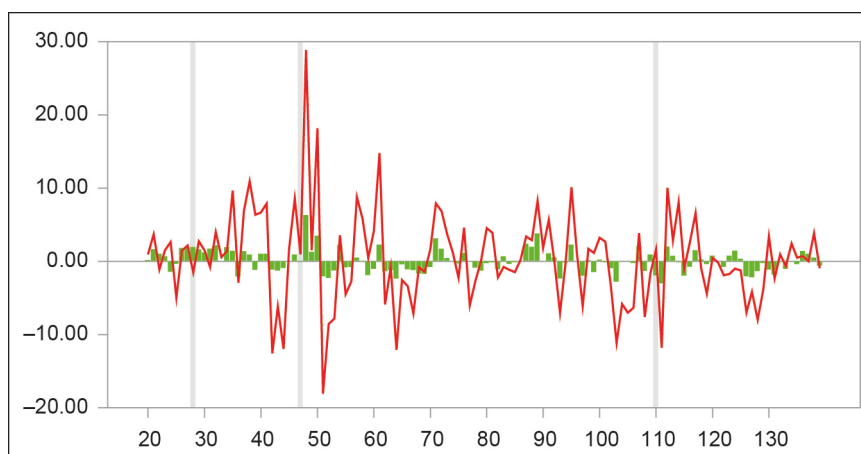
**Figure A18: Contribution of Uncertainty Shock to FX Rate of Thailand**



FX = foreign exchange.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

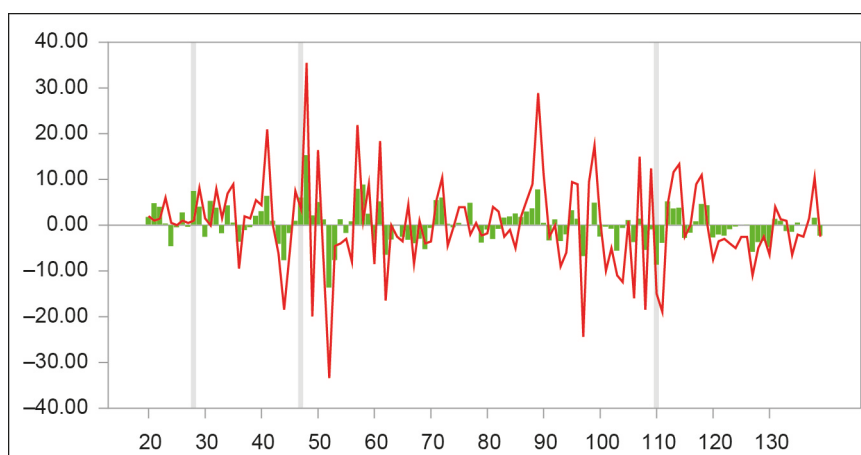
Source: Prepared by author.

**Figure A19: Contribution of Uncertainty Shock to CDS Spread of Turkey**

CDS = credit default swap.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

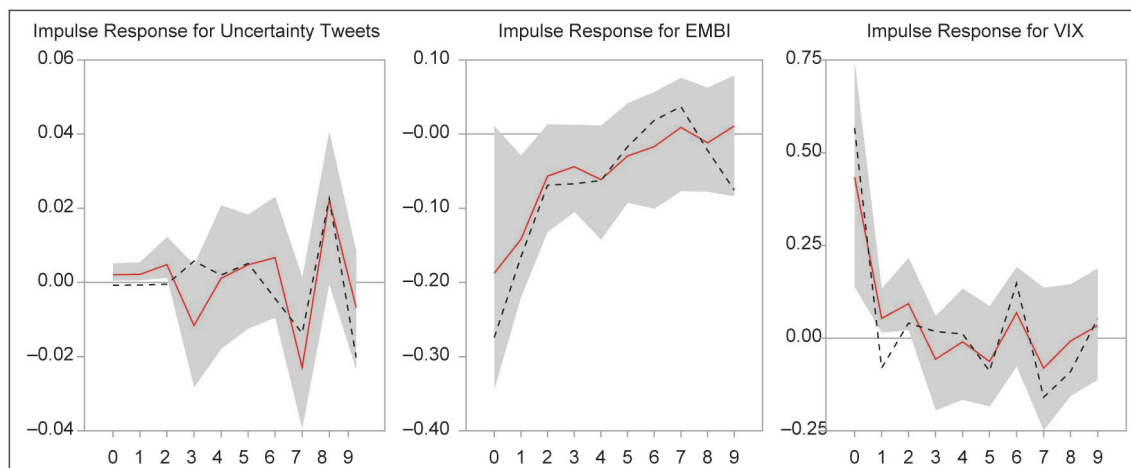
Source: Prepared by author.

**Figure A20: Contribution of Uncertainty Shock to CDS Spread of Indonesia**

CDS = credit default swap.

Notes: The solid line is the realized series. The bars represent the contribution of the uncertainty shock. The shaded areas reflect the testimony of Fed chairman Bernanke on 22 May 2013, the June 2013 FOMC meeting, and the September 2013 FOMC meeting.

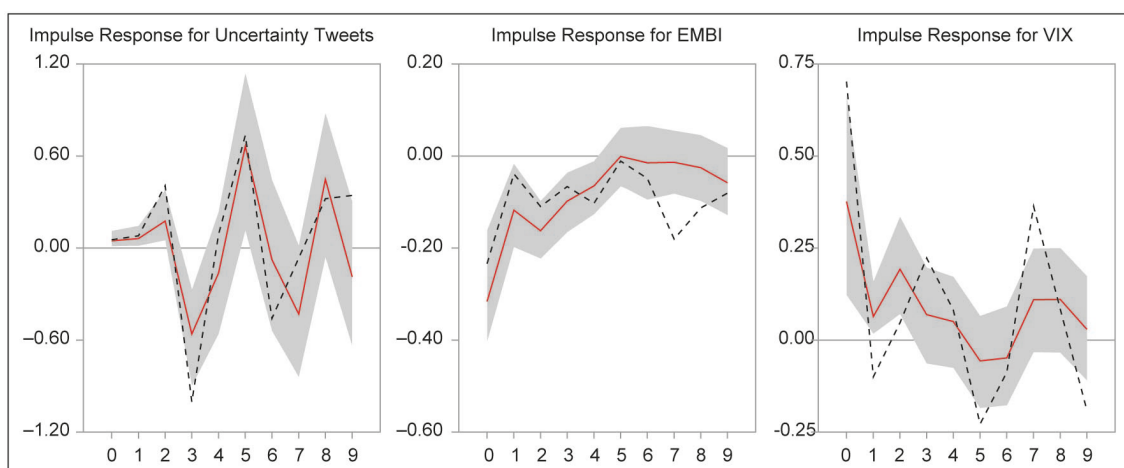
Source: Prepared by author.

**Figure A21: Response of EMBI to Uncertainty Shock with FOMC Dummies**

EMBI = emerging market bond price index; FOMC = Federal Open Market Committee; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

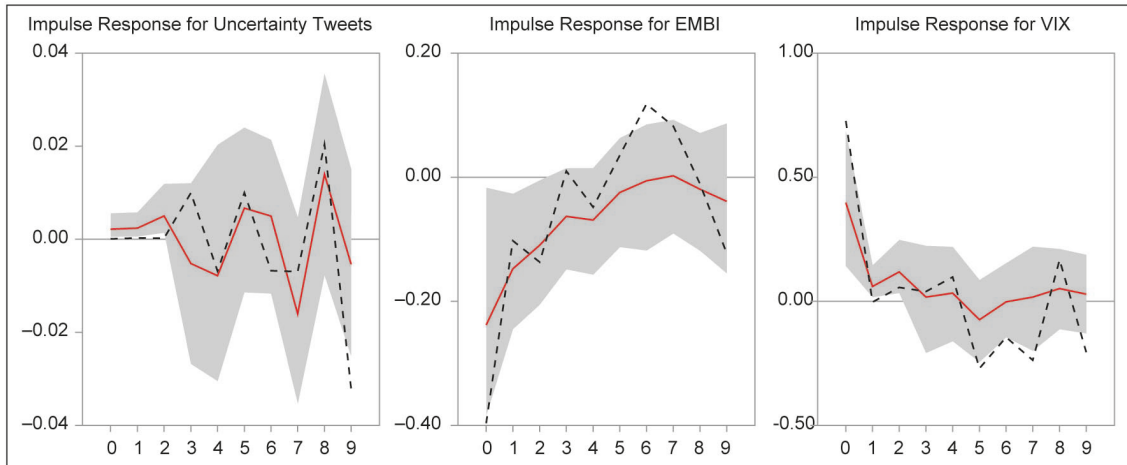
**Figure A22: Response of EMBI to Uncertainty Shock with FOMC Dummies with Weighted Tweets**

EMBI = emerging market bond price index; FOMC = Federal Open Market Committee; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.

**Figure A23: Response of EMBI to Uncertainty Shock with FOMC Dummies with Macroeconomic Fundamentals**



EMBI = emerging market bond price index; FOMC = Federal Open Market Committee; VIX = volatility index.

Notes: The shaded area reflects 68% confidence bands. The red line is the median of all draws; the dotted line is the draw that is closest to the median.

Source: Prepared by author.