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Authors' List

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Quantitative Easing and Tapering Uncertainty: Evidence from Twitter*

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Abstract

In this paper we analyze the extent to which peoples' changing beliefs about the timing of the exit from Quantitative Easing ("tapering") impact asset prices. To quantify beliefs of market participants, we use data from Twitter, the social media application. Our data set covers the entire Twitter volume on Federal Reserve tapering in 2013. Based on the time series of beliefs about an early or late tapering, we estimate a VAR model with appropriate sign restrictions on the impulse responses to identify a belief shock. The results show that shocks to tapering beliefs have profound effects on interest rates, exchange rates and asset prices. We also derive measures of monetary policy uncertainty and disagreement of beliefs, respectively, and estimate their impact. The paper is the first to use social media data for analyzing monetary policy and also adds to the rapidly growing literature on macroeconomic uncertainty shocks.

Keywords: Tapering, unconventional monetary policy, uncertainty, quantitative easing, social media

JEL classification: E32, E44, E52

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1 Introduction

After the 2008 economic crisis, the U.S. Federal Reserve adopted a series of unconventional monetary policy measures in order to enhance credit conditions and support economic recovery. Large-scale asset purchases known as Quantitative Easing (QE) led to a tripling of the Fed's balance sheet.[1] When Federal Reserve Chairman Ben Bernanke, while testifying before the U.S. Congress, first mentioned the possibility of reducing asset purchases on May 22, 2013, markets were wrong-footed. Bernanke's remarks triggered fears of a premature end of asset purchases and an earlier than expected increase in the federal funds rate. Markets coined the term "tapering" to describe the reduction of asset purchases by the Fed and the eventual end of QE.

Market jitters following the May 22, 2013 testimony led to a sharp increase in long-term interest rates in the U.S., a period of high volatility on asset markets and a dramatic appreciation of the US dollar, particularly against emerging market currencies. Since a large part of these turbulences appeared exaggerated and panic-driven, observers referred to the "taper tantrum".

Fed Governor Jeremy Stein (2014) reflects on the revision of investors' expectations and the strong market movements in 2013 which give rise to the "tantrum" notion:

> "In early May 2013, long-term Treasury yields were in the neighborhood of 1.60 percent. Two months later, shortly after our June 2013 FOMC meeting, they were around 2.70 percent. Clearly, a significant chunk of the move came in response to comments made during this interval by Chairman Bernanke about the future of our asset purchase program. Perhaps it is not surprising that news about the future course of the asset purchase program would have a strong effect on markets. But here is the striking fact: According to the Survey of Primary Dealers conducted by the New York Fed, there was hardly any change over this period in the expectation of the median respondent as to the ultimate size of the program. Chairman Bernanke's comments may have clarified the FOMC's intentions, but, according to the survey, they did not have any clear directional implications for the total amount of accommodation to be provided via asset purchases."[2]

[1]See D'Amica et al (2012) and Rogers et al. (2014) for recent surveys on the effectiveness of unconventional monetary policies.

[2]In April 2013, the pessimistic first quartile of Institutions asked by the New York Fed survey of Primary Dealers showed that markets expected the Fed to reduce its monthly purchases of assets worth 85 billion dollars at its December meeting. The events in May 2013 triggered a reassessment of expectations. In the July survey, market professionals were expecting purchases of only 65 billion

In this paper, we provide an empirical analysis of the revision of expectations of market participants and its impact on asset prices which gave rise to the taper tantrum. First, we quantify the response of interest rates, exchange rates and other asset prices to the belief shocks of market participants specific to tapering beliefs. Second, we decompose the dynamics of asset prices in order to isolate the fraction of movements due to changes in tapering beliefs. Third, we measure monetary policy uncertainty as well as derive a measure of disagreement of market participants about future monetary policy and quantify their effects on financial variables.

The primary difficulty of any study addressing sudden changes in beliefs and their consequences is that individual beliefs about the future course of monetary policy are not observable. Survey evidence is typically only available on a very low frequency, thus making an analysis of daily data impossible. An alternative would be to use beliefs extracted from futures prices or the yield curve. The disadvantage is that these market prices do not allow us to extract measures of disagreement of market participants.

In this paper, we offer a new approach to identify shocks to peoples' beliefs about monetary policy by using social media. We use data from Twitter.com, the popular social media application for short text messages ("tweets" of no more than 140 characters). To the best of our knowledge, Twitter data has not been used to study monetary policy before. Many market participants use their Twitter account to express and disseminate their views on the future stance of monetary policy.

The advantage of using Twitter data for research purposes is that (1) users not only receive information but can actively share information, (2) tweets reflect personal views of market participants, (3) tweets can be used to extract not only a consensus view on policy, but also the degree of uncertainty and disagreement about policy, respectively and (4) Twitter users can respond immediately to news about policy such as Bernanke's testimony and also to other Twitter users' contributions. Our data set allows us to track the evolution of market beliefs about monetary policy up to the second.

We use the entire Twitter volume containing the words "Fed"and "taper", which amounts to almost 90,000 tweets for the period April to October 2013. From this we identify tweets that express an explicit view about whether the reduction of bond purchases will occur soon or whether it will occur late. The resulting time series of beliefs of early or late tapering, respectively, are then put into a vector autoregression (VAR) with daily data on interest rates and asset prices. Using appropriate sign restrictions we are able to identify belief shocks and their dynamic effects. In

dollars at the September FOMC meeting and only 50 billion dollars after the December meeting.

addition, we use Twitter data to construct two indexes reflecting the uncertainty and disagreement of future Fed policy and estimate the impact of uncertainty shocks in our VAR model.

The results show that “tapering soon” belief shocks lead to a significant increase in long-term interest rates, a strong drop in stock prices and a persistent appreciation of the U.S. dollar. A prototypical belief shock raises the share of all tweets considering an early tapering by 6 percentage points, leads to a 4 basis point increase in long-term yields and a 4% lower stock market index. In comparison, a belief shock regarding late tapering reduces the long-term rate by more than 3 basis points and induces a persistent increase in asset prices of around 0.3 percentage points. These results are in line with the considerations of Krishnamurty and Vissing-Jorgensen (2013). The data also allows us to study the effects of an increase in uncertainty and disagreement among Twitter users, respectively, on asset prices. Thus, we can shed light on the points raised by Kashyap (2013), stressing the importance of disagreement about the course of tapering unconventional monetary policy.

Understanding market responses to exiting from QE and other unconventional monetary policies is important. Not only is the Fed about to gradually exit from unconventional monetary policy, but the Bank of England and, at some point in the future, the Bank of Japan and the European Central Bank are all on the brink of similar exits from unconventional monetary policies. Clearly communicating exit strategies from unconventional monetary policy to financial markets participants and the general public is essential for a smooth and frictionless return to normal. Analyzing data from social media is a useful way of cross-checking whether official communication was received by the markets as intended. In addition, it is important to quantify the impact of market beliefs on interest rates in light of forward guidance used by many central banks.

The remainder of the paper is organized into 7 sections. Section 2 briefly reviews the related literature. Section 3 introduces our data set on Twitter messages, which is used for the empirical analysis in section 4. The results are discussed in section 5. Section 6 is devoted to the analysis of extensions and the robustness of our results, and section 7 includes our concluding remarks and draws some policy implications.

2 The Literature on Fed Tapering and Uncertainty Shocks

This paper is related to various strands of the literature. Lately, there has been a growing interest in the use of social media (Twitter, Google, Facebook) as a data

source for economic analyses. Among others, Choi and Varian (2009, 2012) use Google Trends data to forecast near-term values of economic indicators such as initial claims for unemployment. Similarly, Askitas and Zimmermann (2009) find strong correlations between Google queries and unemployment rates for Germany.
In the context of financial markets Da et al.(2011) derive a measure of investor attention based on Google search data. Vlastakis and Markellos (2012) find a link between Google keyword searches and stock trading volume and stock return volatility, respectively. Very recently, Dergiades et al. (2014) have shown that social media such as Twitter, Facebook and Google provide significant short-run information for the Greek and Irish goverment bond yield differential. Halberstam and Knight (2014) use data from politically engaged Twitter users to analyze political communication in social networks and Acemoglu et al. (2014) predict protests of Egypt's Arab Spring by a Twitter-based measure of general discontent about the government in power. Our study extends this field of research and is the first that we are aware of to analyze tapering announcements based on Twitter messages.
There are several papers that focus on the impact tapering announcements have on asset prices. A very useful collection of facts related to the responses to tapering news is provided by Sahay et al. (2014).
Eichengreen and Gupta (2013) present the earliest systematic analysis of Fed tapering. They attribute the fluctuations in emerging economies in 2013 to Fed tapering and explain the magnitude of fluctuations in terms of initial macroeconomic conditions. It is shown that better macroeconomic fundamentals did not necessarily shield economies from the tapering fallout.
Aizenman et al. (2014) estimate a panel model with daily data for emerging economies and relate the response to tapering news to macroeconomic fundamentals. Similar to Eichengreen and Gupta (2013) they show that fundamentally stronger countries were more sensitive to tapering and argue that this is due to the massive capital inflows these countries received under the Fed's Quantitative Easing programs. Their paper uses dummies for FOMC meetings during 2013 as a proxy for tapering news.
Nechio (2014) provides descriptive evidence for the adjustment of emerging economies after Bernanke's May 22^{nd} testimony. She finds that the relative strength of emerging markets' responses reflect internal and external weaknesses specific to each market.
Daily data on 21 emerging countries is used by Mishra et al. (2014). In contrast to Eichengreen and Gupta (2013) and Aizenman et al. (2014), their evidence supports the notion that countries with stronger macroeconomic fundamentals experienced a

smaller depreciation of their currencies and smaller increases in borrowing costs. In this study, the market responses are measured in a two-day event window around an FOMC meeting or a publication day of FOMC minutes.

All of these papers proxy market expectations about Fed tapering by impulse dummies reflecting FOMC meetings and chairman Bernanke's testimony, respectively, or by focusing on relatively narrow event windows. They do not measure market expectations directly. This is exactly where our paper adds to the literature. We extract information from Twitter messages to construct a high-frequency indicator of market beliefs. This indicator also reflects changes in policy perception between FOMC meetings and, in particular, mounting uncertainty before FOMC meetings, which cannot be appropriately proxied by meeting dummies.

Closest to this paper is the work by Matheson and Stavrev (2014) and Dahlhaus and Vasishta (2014). The first authors estimate a bivariate VAR model for U.S. stock prices and long-term bond yields. Sign restrictions are used to identify a fundamental-based news shock leading to an increase in both variables and a monetary shock implying an opposite response of stock prices and yields. The authors show that in the taper tantrum episode monetary shocks were important initially, while news shocks became important towards the end of 2013. Our research however measures market expectations from social media and avoids restricting the asset price response. Dahlhaus and Vasishtha (2014) identify a "policy normalization shock" using sign restrictions as one that raises Fed funds futures but leaves current rates unchanged. They show that this shocks has a significant impact on the common component of capital flows to emerging economies.

More generally, our paper adds to the growing body of literature concerned with the macroeconomic consequences of uncertainty shocks. In recent years, researchers develop indicators of uncertainty and analyze the data using VAR models. The first researcher to use this methodology was Bloom (2009). He presents a structural model of macroeconomic uncertainty affecting second moments and estimates a VAR model that replicates the theoretical findings. Baker et al. (2013) focus on uncertainty about future economic policy. They construct an uncertainty index by referring to newspaper articles about uncertainty and show that this index has predictive power for several macroeconomic variables. On a business-level, Bachmann et al. (2013) use German survey data in a VAR model. They find that a heightened degree of uncertainty for businesses correlates to higher unemployment, lower investment and higher refinancing costs.

The only paper so far focusing on monetary developments is Istrefi and Piloiu (2013). The authors use the Baker et al. (2013) index of policy uncertainty for the U.S.,

the UK, Germany and the Euro Area and show that within a structural VAR model uncertainty raises long-term inflation expectations.
In contrast to most of these contributions our measure of policy uncertainty based on Twitter information directly addresses specific uncertainty about the future course of monetary policy.

3 Tapering Beliefs on Twitter

We extract market participants' beliefs and their uncertainty about the future course of monetary policy from Twitter messages. Twitter usage is becoming more and more popular among financial professions. It allows them to comment on policy and market events and to distribute their view to either their followers or even a wider audience in real time.
For the purpose of this study, we obtain the entire Twitter traffic between April 15 and October 30, 2013 containing the words "Fed" and "taper" from GNIP, a provider of social media analyses. The data set includes 87,621 tweets from 27,276 users located in 135 countries and the exact time they were sent.[3] This is a unique data set to study market views during the tapering tantrum episode.
Figure (1) plots the evolution of Twitter traffic over time. It can be seen that the number of tweets increases around Bernanke's testimony and around each FOMC meeting. The use of Twitter peaks at the September 17/18 FOMC meeting, when the Fed finally decided to continue its QE policy and not begin tapering. The sample period covers the entire taper tantrum episode and is sufficiently long to perform a VAR analysis. Further, the data set comprises each tweet's text message of at most 140 characters as well as the name and location of the Twitter user.
In order to shed some light on the distribution of Twitter users and their written messages, Figure (2) illustrates the distribution of tweets generated by different senders on the log scale. For the entire period under consideration we plot the (log) number of users on the ordinate versus the ranked (log) number of tweets on the abscissa. Obviously, the resulting graph resembles a Zipf-like distribution, indicating that a small number of active users frequently share their opinions about the Fed's future policy stance and that a large number of users generate tweets about Fed tapering rather infrequently. Excluding retweets, see Figure (2), does not change the distributional properties of the data.
In order to contribute along several dimensions the tweets are then separated into

[3]Retweets are included in this figure. For the purpose of this paper we interpret retweeted messages as an endorsement of the initial message's relevance and include it in our measure of beliefs.

those expressing the belief of an early tapering, probably in the summer of 2013 or at the September 2013 FOMC meeting, and those expressing the belief of tapering occurring later. A two-step procedure is used to interpret the content of tweets and allocate the tweets to $Tweets_t^{soon}$ and $Tweets_t^{late}$. In a first step, Tweets are filtered according to a list of predefined keywords. In a second step, all remaining tweets are, if appropriate, manually allocated to one of the two categories. The appendix goes into more details about this procedure. As a result, we are left with 22,000 tweets which contain explicit views about future policy. Tweets that could not be assigned to one of those two categories mostly comment on market movements, point to the upcoming FOMC meeting or formulate unspecific policy views (i.e. "to taper or not to taper"). Finally, the tweets are aggregated into daily series of beliefs.
As examples, consider the following tweet written on May 20, 2013:

"Job market gains could lead Fed to taper QE3 early"

This is taken to reflect the view of an early tapering and is allocated to $Tweets_t^{soon}$. Likewise, consider this tweet written on July 31, 2013:

"The Case For A September Fed Taper Just Got A Whole Lot Stronger"...

This tweet is also counted as reflecting the view that the Fed will taper early. The following tweets, in contrast, suggest the Twitter users believe in a later tapering decision: On May 21, 2013, a tweet states that

"Fed's Bullard says doesn't see a good case for taper unless inflation rises ..."

and on September 18, 2013 it is retweeted that

"RT @DailyFXTeam: Economist Nouriel Roubini tweets that based on weak macro data, the Fed shouldn't taper today."

Figure (3) depicts the identified belief series. We clearly see sizable fluctuations in beliefs and the increased volatility before and after FOMC meetings. Our data contains a total of 7687 tweets referring to early tapering and 14,555 tweets that are associated with tapering late. Furthermore, the majority of tweets initially expressed the belief of an early tapering, which than changes in September 2013 in favor of a late tapering. Interestingly, both series, $Tweets_t^{soon}$ and $Tweets_t^{late}$ peak during the September 18^{th} meeting of the FOMC, and are positively correlated with a correlation coefficient of 0.4, with a total of 436 and 1181 tweets, respectively. The contents of the two belief series are visualized through word clouds, see figures (5) and (6).

Beliefs of an early or a late tapering could fluctuate within the same day, indicating that there is substantial heterogeneity in market participants' beliefs about future policy. This possibility encouraged us to construct two additional indicators that reflect the uncertainty and the disagreement between market commentators about future policy. The uncertainty indicator, $Tweets_t^{uncertainty}$, is constructed by counting specific words reflecting uncertainty as in Loughran and McDonald (2011). Details about the construction are also given in the appendix. Figure (4) plots the uncertainty indicator. Like the other belief series, uncertainty also seems to be sensitive to official Fed communication.

In the regressions below, we include our belief proxies $Tweets_t^i$ as a fraction of the total amount of tweets on a particular day, $Tweets_t$ i.e.

$$Beliefs_t^i = 100 \times \frac{Tweets_t^i}{Tweets_t}$$

where $i = \{soon, late, uncertainty\}$.

A fourth indicator measures market participants' diverging views about the short-term path of monetary policy. This measure of disagreement, $Beliefs_t^{disagreement}$, is based on previously identified soon/late belief series and is defined as

$$Beliefs_t^{disagreement} = 1 - \sqrt{\left(\frac{Tweets_t^{soon}}{Tweets_t} - \frac{Tweets_t^{late}}{Tweets_t}\right)^2}.$$

It reaches its maximum value of 1 for cases in which the fraction of beliefs corresponding to early tapering is equal to the fraction of beliefs referring to later tapering. If one opinion concerning future monetary policy dominates the other, however, both fractions diverge, and the disagreement index declines. In the following we will use fluctuations in tapering beliefs in a vector autoregressive model to identify unexpected shocks to tapering expectations, policy uncertainty and investor disagreement.

4 The Model

Vector autoregressive models are well suited to analyze the consequences of shocks to people's beliefs. In our model specifically, unexpected changes in their views about the Fed's propensity to taper. Our estimation strategy is to use a standard VAR model and place the series of extracted tweets next to a measure of long-term interest rates, an index of implied volatility as a proxy for fluctuations in risk aversion and asset prices. Such a small-scale VAR model is able to provide evidence about how belief shocks affect financial conditions.

4.1 The VAR Model

Our structural VAR model is assumed to have the standard form

$$B(L)Y_t = \varepsilon_t, \quad \text{with } E[\varepsilon_t \varepsilon_t'] = \Sigma_\varepsilon$$

where $B(L) \equiv B_0 - B_1 L - B_2 L^2 - ... - B_p L^p$ is a p^{th} order matrix polynomial in the lag operator L, Y_t a k-dimensional time series of endogenous variables and ε_t represents a serially uncorrelated prediction error with Σ_ε as its variance-covariance matrix. Typically the variance-covariance matrix of the structural innovation is normalized to $E(\varepsilon_t \varepsilon_t') \equiv \Sigma_\varepsilon = I_k$. A reduced-form representation for this system of equations is

$$A(L)Y_t = u_t, \quad \text{with } E[u_t u_t'] = \Sigma_u.$$

where $A(L) \equiv I - A_1 L - A_2 L^2 - ... - A_p L^p$ reflects the matrix polynomial and u_t constitutes a white noise process with variance-covariance matrix Σ_u.

The reduced-form model is estimated on the following vector of endogenous variables at a daily frequency

$$Y_t = \left(Beliefs_t^j, Rate_t, VIX_t, AssetP_t\right)'$$

where $Beliefs_t^j$ with $j = \{soon, late, uncertainty, disagreement\}$ reflects tapering belief proxies, $Rate_t$ indicates the 10-year, 5-year or 2-year, constant maturity Treasury bill rate, VIX_t is the index of implied stock market volatility which is typically used as a proxy for risk aversion and $AssetP_t$ is a (log) asset price which we take out of a list of alternative asset price variables. The list includes the S&P 500 stock market index, the Dow Jones stock market index, the NASDAQ stock market index, the USD exchange rate against the Euro, the trade-weighted USD exchange rate against major trading partners and a broad trade-weighted USD exchange rate.[4]

We fitted the VAR model to the data by including a constant and 10 lags of the endogenous variables. All weekends and holidays for which no financial data is available are excluded. The sample period consists of 138 daily observations and covers April 15, 2013 to October 30, 2013 and is sufficiently long for reliably estimating a VAR.

[4]All data is taken from the FRED database of the St. Louis Fed.

4.2 Identification

The identification of belief shocks is crucial for this analysis. As the contemporaneous interaction among all variables at a daily frequency prevents us from using a triangular identification scheme, sign restrictions (Uhlig, 2005) provide a useful alternative to identify a structural shock in this VAR analysis. In a sign restrictions approach identification is achieved by imposing ex post restrictions on the signs of the response of the endogenous variables to a structural shock, e.g. our belief shock. We believe that using sign-restrictions creates a VAR best suited to analyze the mutual interaction between market beliefs about policy, asset prices and volatility indicators even though most of the literature on uncertainty shocks rely on triangular identification schemes instead (such as Bloom (2009) and Baker et al. (2013) reviewed in section 2).

In order to identify economically meaningful structural shocks, ε_t, we need to find a matrix B_0^{-1} such that the structural innovations are linked to the reduced-form shocks by $u_t = B_0^{-1}\varepsilon_t$, and $\Sigma_u = B_0^{-1}\Sigma_\varepsilon B_0^{-1\prime} = B_0^{-1}B_0^{-1\prime}$ with $\Sigma_\varepsilon = I_k$ holds.

We proceed in the following way: We estimate our model by OLS which provides us the reduced-form coefficients $A(L)$ and the covariance matrix Σ_u. Since it is $P_c^{-1} = chol(\Sigma_u)$ so that $\Sigma_u = P_c^{-1}P_c^{-1\prime}$ and $\Sigma_u = P_c^{-1}\tilde{S}\tilde{S}' P_c^{-1} = B_0^{-1}B_0^{-1\prime}$ with $B_0^{-1} = P_c^{-1}\tilde{S}$ respectively, we randomly draw a matrix $\tilde{S}$ from a space of orthonormal matrices. Further, we calculate impulse response functions for the restricted periods as $D(L) = A(L)^{-1}B_0^{-1}$ and check whether they satisfy the postulated sign restrictions. We discard those response functions that fail to meet the restrictions while a new orthonormal matrix and new impulse responses are drawn. This procedure is continued until 500 accepted impulse response functions are stored for which we then compute impulse response functions for all desired periods.

The impact restrictions we use to identify a belief shock are summarized in Table (1). We estimate several VAR models, one for each alternative series of beliefs and our measures of uncertainty and disagreement, respectively.

Table 1: Sign restrictions to identify a belief shock

	$Beliefs_t^j$	$Rate_t$	VIX_t	$AssetP_t$
model I: soon	+	+	+	
model II: late	+	-	-	
model III: uncertainty	+		+	
model IV: disagreement	+		+	

The belief shock is identified by imposing positive responses of $Beliefs_t^j$ for all

different proxies presented before. A shock to "tapering soon" beliefs in model I is interpreted as raising the respective belief series, leading to higher bond yields and implying a higher level of implied volatility. These restrictions are imposed only for one period, i.e. the day of heightened Twitter activity. We do not restrict the responses for the included asset prices but expect a belief shock to depress stock prices and to lead a depreciation of foreign currencies against the USD.[5] A shock to "tapering late" beliefs in VAR model II should lead to the opposite responses.
Since we do not know how shocks to uncertainty and disagreement effect the long-term interest rate we abstain from restricting those responses in our models III and IV. We assume, however, that both are associated with an increase in market volatility as reflected by the VIX index. Although we do not derive the restrictions from a particular asset pricing model, it seems plausible that any increase in policy uncertainty or a more marked disagreement among investors is associated with a higher implied volatility. For models III and IV we impose two restrictions for two periods.

5 Results

In this section we present the impulse responses following a shock to tapering beliefs, tapering uncertainty or disagreement about tapering, respectively, as identified by the sign restrictions. Figures (7) to (26) show the median responses of the variables to a belief shock of one standard deviation in size for a horizon of 20 days after the shock. Additionally, we show the 16^{th} and 84^{th} percentiles of all accepted impulse responses.

5.1 Shocks to Tapering Beliefs

Our benchmark results are presented in Figures (7) to (20) which reflect the responses of the long-term U.S. interest rate, the VIX index and the S&P 500 stock market index to various belief shocks. After a positive shock to "tapering soon" beliefs as depicted in Figure (7), the VIX index whose reaction is restricted to be positive for the first period, increases by about 0.5 percentage points and stays significantly positive for another four periods. The long-term interest rate rises initially less strongly, peaks at 0.04 percentage points and shows a persistent positive reaction throughout the complete horizon. This indicates that a shift in beliefs of an

[5] Since our measure of Twitter beliefs does not include obvious comments on market movements but only firm views on the timing of tapering, we are confident that we can exclude problems of reverse causality.

early tapering, demonstrated by a 5% increase of Twitter users foreseeing an early tapering, leads to a substantial tightening of monetary conditions. Importantly, our one-day restriction on the direction of the response of bond yields seems to impose a fairly weak constraint on adjustment dynamics. The resulting adjustment is typically not completed after the 20-day horizon depicted here. The immediate and persistent response of asset prices to tapering beliefs is in line with the arguments discussed by Krishnamurty and Vissing-Jorgensen (2013).

Since some days are characterized by a much stronger swing in beliefs, our model shows that belief shocks explain a large fraction of the increase in bond yields. Following a belief shock, we find a drop in asset prices, although this reaction is statistically significant only for one day. With a drop by 0.4%, stock prices appear to be very sensitive to tapering beliefs.

A key feature of our Twitter data set is that we can use the heterogeneity of users' beliefs to distinguish between "tapering soon" belief shocks and "tapering late" belief shocks. In model II we therefore use the fraction of users expressing a late-tapering belief. Note that by construction, $Tweets_t^{soon}$ and $Tweets_t^{later}$ are *not* perfectly negatively correlated. Hence, we can estimate the VAR model for late-tapering beliefs in order to compare the strength of the responses to $Tweets_t^{soon}$ and $Tweets_t^{later}$. We obtain inverse results for responses to a "tapering late" belief shock. Market volatility and the long-term interest rate decrease. It can be seen from Figure (8) that a "tapering late" belief shock induces a persistent positive response of the S&P 500. Broadly speaking, the responses to "tapering soon" or "tapering late" belief shocks appear symmetrical, early tapering beliefs increase market volatility and long-term interest rates, while late tapering beliefs cause an inverse response, with a slight tendency for asset prices to respond more significantly to beliefs of late tapering.

For specifications in which the long-term rate is replaced by (i) the 5-year and (ii) the 2-year constant maturity Treasury bill rate, similar results can be obtained. A "tapering soon" shock, by assumption, raises market volatility on impact and induces a persistent increase in the 5-year and 2-year interest rate, respectively. In the short term asset prices drop significantly by about 4 basis points. In contrast, a "tapering late" shock induces inverse responses that appear to be more persistent and especially more significant for asset prices, see Figure (17) to Figure (20).

Figures (13) to (16) depict the responses of the trade weighted U.S. dollar against a broad set of currencies (TWEXB) and the trade weighted dollar against major currencies (TWEXM). For both specifications we see significant reactions to shocks in "taper soon" beliefs or "taper late" beliefs. Again the dollar appreciates following a revision of beliefs towards an early tapering and depreciates after a shock to a later tapering. Figures (13) and (15) suggest an initial boost in long-term rates by about 0.025 percentage points followed by a rapid increase up to 0.04 percentage points induced by a shock to beliefs of early tapering. This response, again is analogous to the benchmark model. In addition, an appreciation of the dollar is apparent. The opposite situation is shown in Figures (14) and (16) where a shock to beliefs of later tapering reduces the interest rate persistently by 2 and 3 basis points, respectively and results in a depreciation of the U.S. dollar. Whereas we observe substantial persistence for about eight days in the reaction of the TWEXB, the response for TWEXM appears to be less persistent.

5.2 Shocks to Uncertainty and Disagreement

While the previous subsection studied shifts in the share of Twitter users believing in an early or late tapering, we now analyze the effect of uncertainty and disagreement in beliefs. Figure (21) and Figure (22) show the results for a shock to the uncertainty and the disagreement indices described in section (3). For these two specifications no restrictions are imposed on the long-term interest rate and the asset price in order to let the data speak freely.

Interestingly an uncertainty shock decreases the interest rate persistently by around 0.02 percentage points which is in line with the findings of Leduc and Liu (2012), while a shock to the disagreement index shows no effect on the interest rate.[6] Nevertheless, asset prices fall significantly in the medium-term when there is greater disagreement among market participants.

In a VAR setting in which the S&P 500 stock market index is replaced by the NASDAQ Composite, which mainly tracks technology stock, our results remain nearly unchanged both in terms of the dynamics and magnitudes. However, here a shock to disagreement provokes a swift reaction of the stock market index whereas in the previous model the stock market index response was more sluggish. This can be seen in Figure (24). Our findings are consistent with the view that the NASDAQ Composite tends to be more volatile than the S&P 500. Furthermore, in this specification we cannot confirm a drop in long-term interest rates after an uncertainty shock as shown in the benchmark model.

We now modify our model and substitute asset prices with the dollar/euro exchange rate, shown in Figures (25) to (26). Shocks to uncertainty influence the exchange rate positively, i.e. the dollar depreciates by 0.2 percentage points. We do not report the results for an uncertainty or disagreement shock on the trade-weighted exchange

[6]Bekaert et al. (2013) also use a VAR model and find a negative and persistent effect of uncertainty shocks on the real interest rate.

rates since these responses lack statistical significance.

From these results we conclude that shifts in investors' uncertainty or in their disagreement are a separate and important factor in the dynamics of interest rates and asset prices. This is in line with Kashyap's (2013) argument. As mentioned before, these results link our study to the literature on the tapering tantrum and also on the effects of uncertainty shocks.

In a last step we report the contribution of our set of belief shocks to the forecast error variance of the variables in the benchmark specification, i.e. including the 10-year interest rate, the VIX index and the S&P 500, see Table (5). As can be seen from the table, there is a substantial impact on all three series based on the median estimate of the responses. We find that for all horizons considered a share of around 20% of the variation in all three variables is due to a belief shock. This underlines the quantitative importance of shifts in market beliefs for asset prices. Moreover, shocks to uncertainty and disagreement appear to be as important as shifts in expectations of an early or late tapering.

6 Robustness

In this section, we analyze the robustness of our findings. For that purpose we respond to the Fry and Pagan (2007) critique concerning vector autoregressions with sign restrictions, we discuss the results for alternative measures of expectations of market participants, we estimate an alternative model specification and, finally reconsider the role of official Fed communications for the information content of our beliefs.

As the identification of structural shocks with sign restrictions delivers impulse responses drawn from a set of different models, a critique raised by Fry and Pagan (2007), reporting the median responses only, may be infeasible and misleading. Therefore, we check the robustness of our findings with the benchmark model shown in the previous section. For this purpose we focus on those responses that are drawn from a single structural model and that minimize the sum of the square distance from the median response. In Figure (27) and Figure (28) the median impulse responses are represented as solid lines while the closest-to-median responses are depicted as dashed lines. Interestingly, the primary results are fundamentally untouched. It can be seen that while the dynamic effects of a belief shock remain unchanged, it is only the magnitude of all responses that increases noticeable. Our previously presented results can be interpreted as a conservative estimate of the effects of belief shocks. However, we continue with our robustness analysis by focusing on only the median responses.

Next, we compare the results of our baseline model by replacing the data by Twitter beliefs constructed in a way that excludes retweets. Thus, we only include original messages and exclude messages forwarded by other users. It can be seen from Figure (29) and Figure (30) that our benchmark results found in section (5.1) are still robust even when excluding retweeted messages. Both specifications of user beliefs deliver almost the same results. This also implies that beliefs expressed through Twitter messages move markets, but that the cascade of retweeted messages is of minor importance for financial markets.

In addition, we refitted the baseline model for lag lengths of one and five, respectively. Again, our findings appear to be robust regarding those variations. For the latter case Figure (31) and Figure (32) show that the impulse responses from a VAR(5) differ in their dynamics compared to the VAR(10) but are nearly identical in their magnitude. The same is true for a VAR(1) specification depicted in Figures (33) and (34). From this we conclude that our results are not sensitive to the choice of the lag order or the estimated VAR system.

Figure (3) shows that our belief series peak on days of FOMC meetings. One could argue that the information content of Twitter beliefs stems from the fact that they simply reflect the official Fed communication. To evaluate the information content, we follow a two-step approach. In the first step, $Beliefs_t^{soon}$ is regressed on a set of dummies reflecting the FOMC meeting in April, June, July, September and October 2013, the days on which the minutes of past FOMC meeting are published and the day of Ben Bernanke's testimony in Congress. The residual can be interpreted as the part of beliefs which is not explained by these Fed events. In a second step, we replace the belief series in our VAR model by this series of residual beliefs. Figure (35) presents the resulting impulse responses. We see that our main findings remain unchanged. The bond yield responds to a belief shock as strongly as before. Thus, the information incorporated in the Twitter traffic remains important for asset prices, even after Fed communication is removed from our belief series.

7 Conclusions

This paper provides an empirical analysis of the taper tantrum episode of U.S. monetary policy, in which the expectations of a premature normalization of policy caused global market jitters. The analysis is based on a unique data set consisting of 90,000 Twitter messages on Fed tapering which we use to build series of investors' beliefs about an early or late tapering. A series of VAR estimates showed that shocks to market beliefs derived from Twitter messages have strong and persistent effects on bond yields, exchange rates and asset prices. The paper is the first study on monetary policy using social media data.

The implications of the findings are threefold. First, our results show that beliefs about exiting QE have contractionary effects on asset prices. This is additional evidence that announcing QE had the intended expansionary effects in the first place.

Second, we show that market sentiment reflected in individual text messages matters for asset prices. Many papers use market prices such as Fed funds futures or the yield curve to model expectations of future policy. However, market prices do not allow the researcher to extract information on the uncertainty of the policy outlook or the disagreement among market participants. Twitter data, which we used to show that beliefs of an early or a late tapering could change in the same day, allows such an analysis. Given the ubiquity of social media data and the ability to deal with a large data volume make the usage of this kind of data an interesting field for future studies in monetary policy.

Third, the study sheds light on the importance of explicitly communicating an exit from unconventional monetary policy measures and offers some quantitative evidence to policymakers. Since many central banks such as the European Central Bank or the Bank of Japan are still heavily engaged in asset purchases and other unconventional policy measures, the challenges of preparing markets for the exit from those policies are yet to come. In this sense the taper tantrum episode of U.S. policy provides valuable lessons that may allow other central banks to avoid exceptional market volatility.

Moreover, our study stands out from many others that analyze the influence of social media on financial markets, because of the uniqueness of our data set. To our knowledge, most of the existing literature rely on, at best, daily data and volume only. In comparison to that our data set comprises each tweet's text message, the exact timing the tweet was sent as well as the name and location of the Twitter user. Hence, we are able to exploit the data in several dimensions. Given the speed at which news and information travel it would be tremendously interesting to analyse the high-frequency impact of tapering beliefs during and around the FOMC meeting days. In any case, this is one task for further research.

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8 Appendix

Here we describe our procedure of constructing our series of market beliefs, $Tweets^{soon}$ and $Tweets^{late}$, from our set of 87,621 Twitter messages that had been prefiltered out of the entire Twitter traffic by the words “taper” and “Fed”.

We prepare our dataset by discarding a small number of tweets written in a language other than English. Then we take into account the fact that tweet data is given in UTC time while all other series, especially asset prices, are based on New York time. Hence, for an adequate estimation of our model it is required to harmonize the timing. Since UTC time is four hours ahead of New York time we subtract four hours from UTC time to standardize it to New York time. As a consequence, tweets that were posted between 12:00 am and 3:39 am are now assigned to the previous day.

Further, we use a two-step approach to separate beliefs of early tapering from those of late tapering. In a first step, we employ dictionary methods that allow to filter tweets according to a list of predefined keywords. Table (2) and Table (3) show the selected keywords for the categories “late” and “soon”, respectively.

Table 2: Predefined keywords for category "late"

Late (until September 18, 2013)		Late (from September 19,2013)	
2014		2014	
backed away		backed away	
bluff	incl. bluffing	bluff	incl. bluffing
dampen		dampen	
delay	incl. delayed	delay	ink. delayed
December		*March*	
debt ceiling		debt ceiling	
doesn't soon		doesn't soon	
doesn't taper		doesn't taper	
dove	incl. dovish	dove	incl. dovish
Dudley		Dudley	
ease fears		ease fears	
end of the year		end of the year	
in 3rd		*in 1st*	
increase		increase	
isn't happening		isn't happening	
isn't soon		isn't soon	
later in 2013		later in 2013	
less	incl. less likely	less	incl. less likely
no exit		no exit	
no taper		no taper	
not enough		not enough	
not exit QE		not exit QE	
not fast		not fast	
not so fast		not so fast	
not soon		not soon	
not yet		not yet	
November		*February*	
October		*January*	
shutdown		shutdown	
six months		six months	
third		*first*	
this year		not this year	
too soon		too soon	
until		until	
weak	incl. weakness	weak	incl. weakness
will not		will not	
will not taper off		will not taper off	
will take		will take	

It can be seen that both categories are separated into a list of keywords pre and post September 18, 2013. This differentiation is necessary because some keywords imply tapering beliefs that depend on the date the corresponding tweet was sent i.e., a tweet that includes the keyword "December" posted in May corresponds to expectations of a late tapering while another tweet also referring to "December" but posted in October indicates an early tapering. Keywords that have this property are written in italics. We choose September 18, 2013 as our critical date because of the significant shift in tapering expectations that occurred after the September FOMC meeting shown by Figure (1).

For cases in which the tweets contain negations or keywords from both categories, our dictionary method is not able to allocate tweets to one of the two specified categories. Nevertheless, those tweets are identified by the algorithm which allows us, in a second step, to check and assign them manually.

Table 3: Predefined keywords for category "soon"

Sooner (until September 18, 2013)		Sooner (from September 19, 2013)	
		2013	
begin		begin	
can taper		can taper	
confidence		confidence	
could taper		could taper	
drop		drop	
early		early	
end eas	incl. end easing	end eas	incl. end easing
		end of the year	
expects to taper		expects to taper	
exit qe		exit qe	
fall		fall	
faster		faster	
		fourth	
		4th	
fuel		fuel	
ready		ready	
fell		fell	
Fisher		Fisher	
good news		good news	
hawk	incl. hawkish	hawk	incl. hawkish
in next		in next	
increasing expectations		increasing expectations	
June		June	
July		July	
August		August	
Lacker		Lacker	
likely		likely	
low unemployment		low unemployment	
lower unemployment		lower unemployment	
may begin		may begin	
may soon		may soon	
may taper		may taper	
midyear		midyear	
next few		next few	
newt meeting		newt meeting	
		November	
now taper		now taper	
ought to taper		ought to taper	
Plosser		Plosser	
pressure		pressure	
quicker		quicker	
reduce		reduce	
refine	incl. refining	refine	incl. refining
rumour		rumour	
septaper		septaper	
September		September	
set to taper		set to taper	
should taper		should taper	
slow down		slow down	
soon	incl. sooner	soon	incl. sooner
soonish		soonish	
still		still	
summer		summer	
talk ongoing		talk ongoing	
taper hint		taper hint	
taper sooner		taper sooner	
taper talk		taper talk	
this summer		this summer	
unemployment drops		unemployment drops	
unemployment falls		unemployment falls	
unemployment fell		unemployment fell	
urge	incl. urged	urge	incl. urged
will taper off		will taper off	
will taper QE		will taper QE	
within months		within months	
would taper		would taper	
		December	

Table 4 contains keywords that are used to identify a series reflecting uncertainty as in Loughran and McDonald (2011). Basically, this procedure is similar to the procedure that is outlined above, except there is no need to create pre and post September 18^{th} categories for the specified tweets. For the entire sample it is sufficient to utilize a constant list of keywords.

Although the dictionary approach to the content analysis of tweets is not immune to mistakes, we believe that in the aggregate the resulting belief series are representative for the true beliefs of Twitter users. For every wrongly coded "early taper" belief there might be a wrongly coded "late taper" belief. Aggregated over the day these errors will potentially offset.

Table 4: Predefined keywords for Uncertainty (Loughran and McDonald (2011))

from April 14, 2013 until October 30, 2013

pending	seems	undetectable	unsettle
perhaps	seldom	underditermin	unspecifi
possib	sometime	undocumentes	untestes
precaution	somewh	unexpect	unusual
predict	speculat	unfamiliar	unwritten
preliminar	sporadic	unforecasted	vagaries
presum	sudden	unforseen	vague
probab	suggest	unguaranteed	variab
random	suspect	unhedged	varian
reassess	tend	unidentifi	variat
recalculat	tentativ	unknown	varie
reconsider	turbulence	unobservable	vary
reexamin	uncertain	unplanned	volatil
reinterpret	unclear	unpredictable	likelihood
revise	unconfirmed	unprove	anticipat
risk	undecided	unquantifi	clarification
roughly	undifined	unreconciled	
rumors	undesignated	unreasonabl	

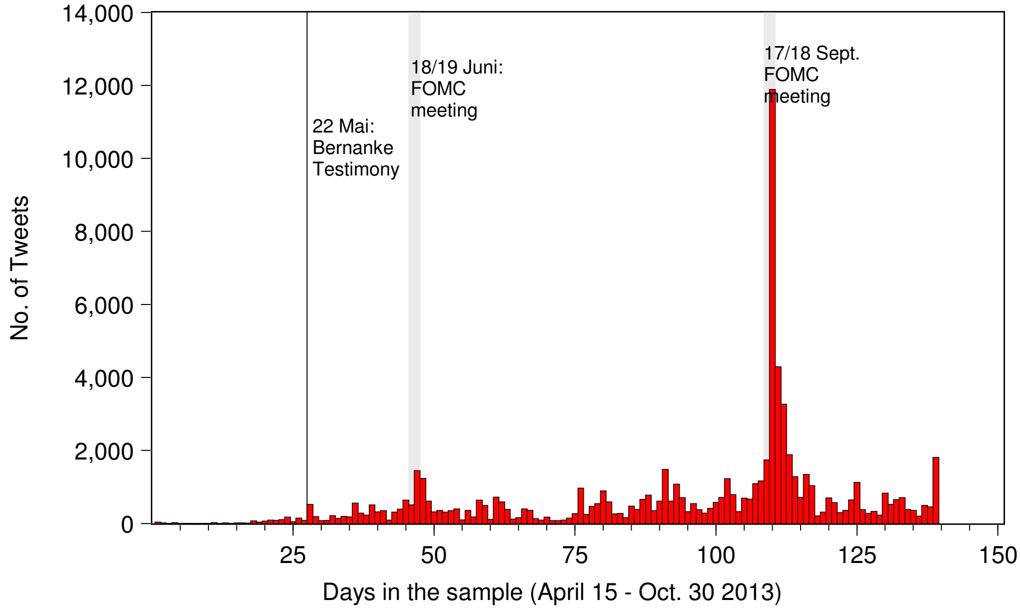

Figure 1: All tweets containing "Fed" and "Taper"

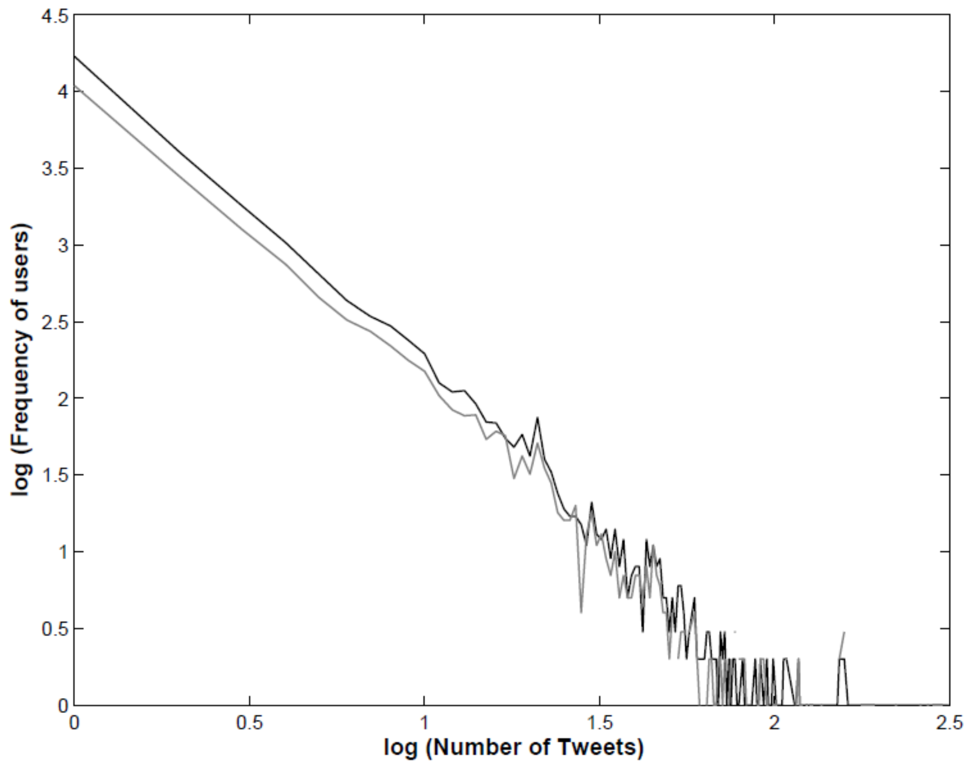

Figure 2: Distribution of all tweets (black) and all tweets excluding retweets (grey) and users in log scale

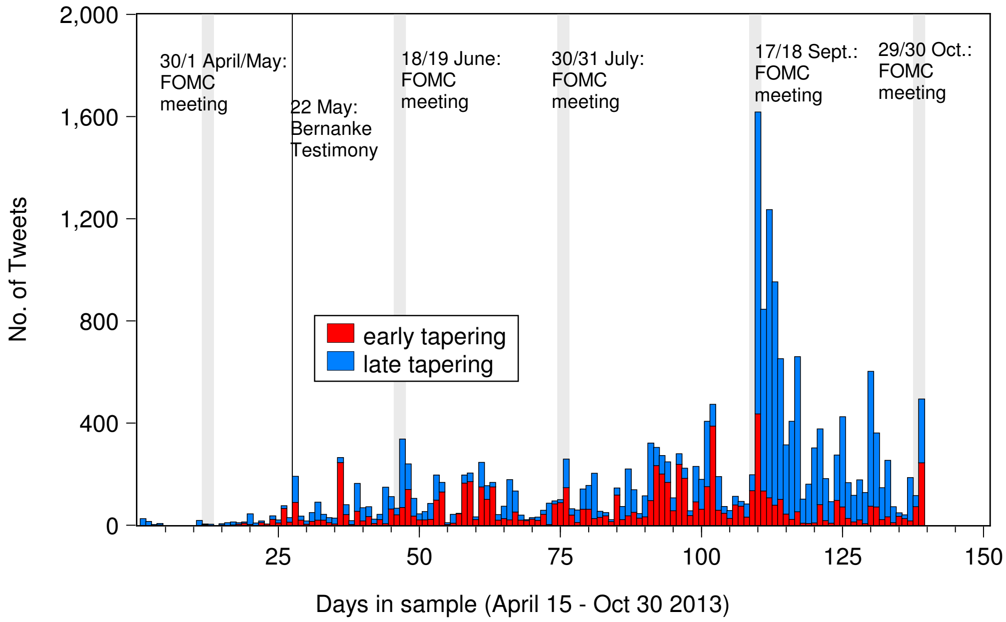

Figure 3: Tweets expressing beliefs on soon/late tapering

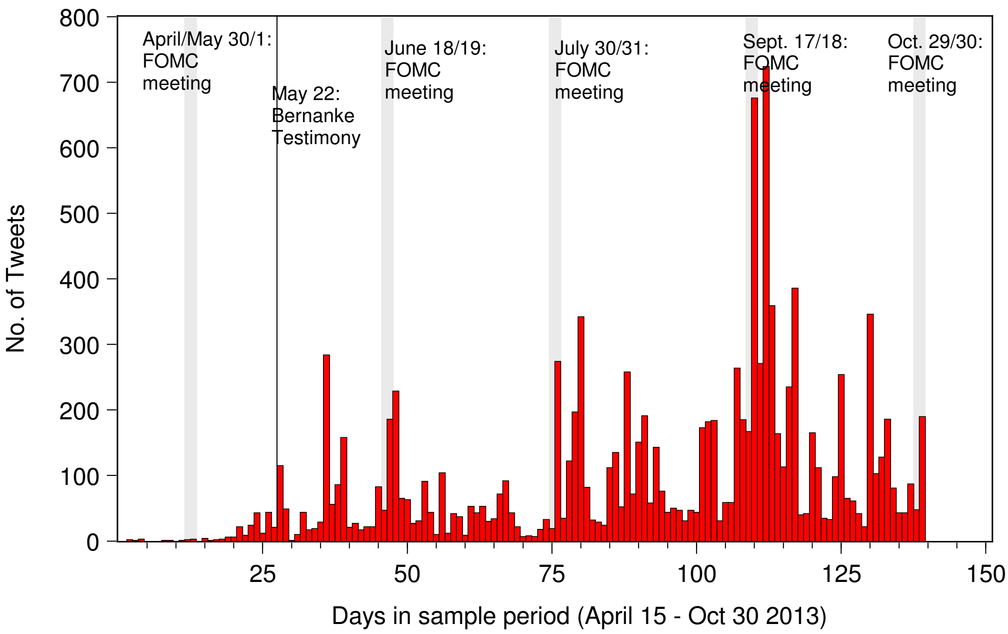

Figure 4: Tweets expressing uncertainty about tapering

Figure 5: Content (excl. "Fed" and "taper") of tweets expressing beliefs on early tapering

Figure 6: Content (excl. "Fed" and "taper") of tweets expressing beliefs on late tapering

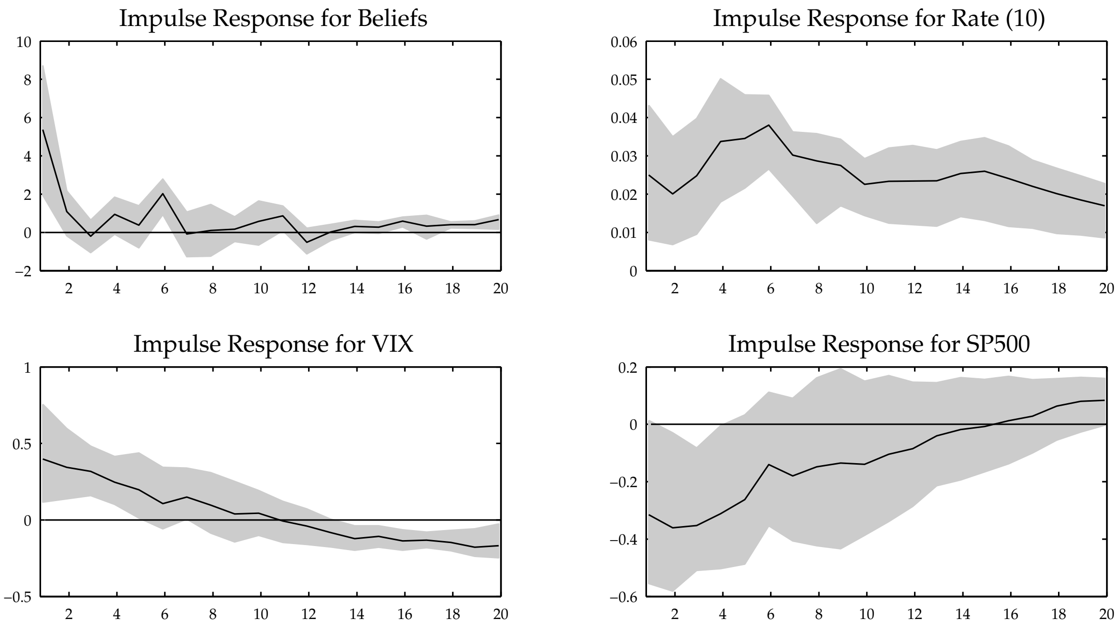

Figure 7: Impulse responses to shock to beliefs of early tapering: S&P500

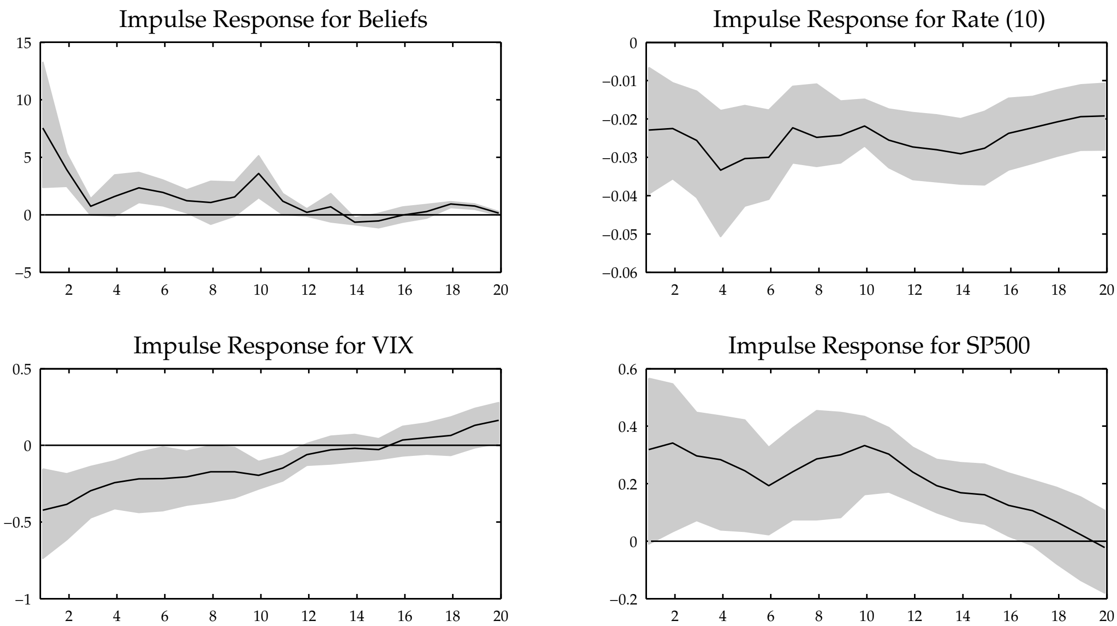

Figure 8: Impulse responses to shock to beliefs of late tapering: S&P500

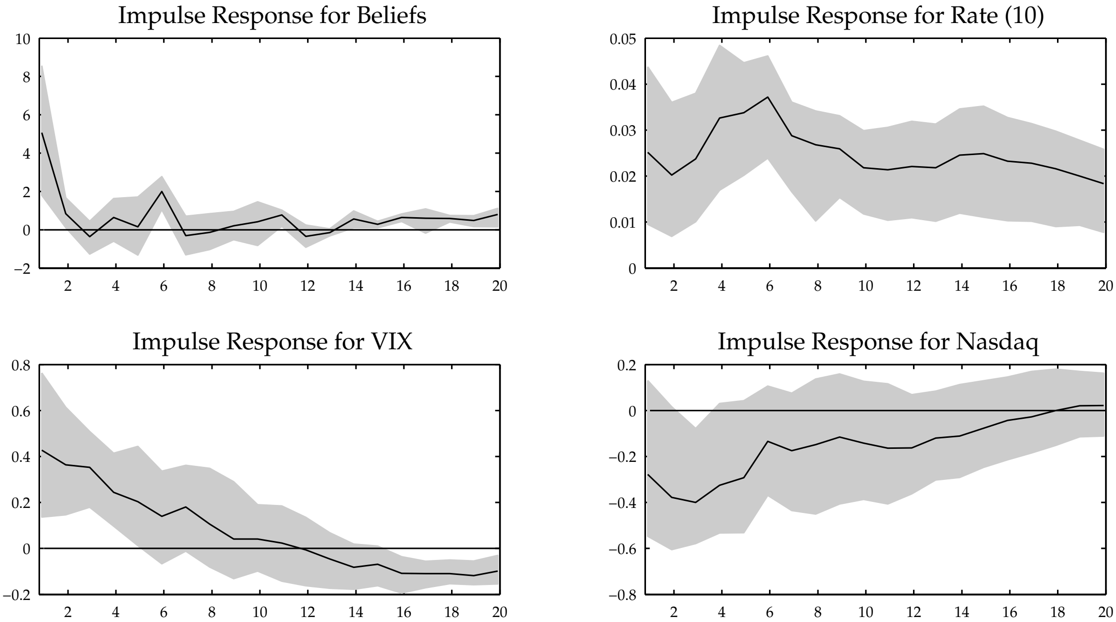

Figure 9: Impulse responses to shock to beliefs of early tapering: NASDAQ

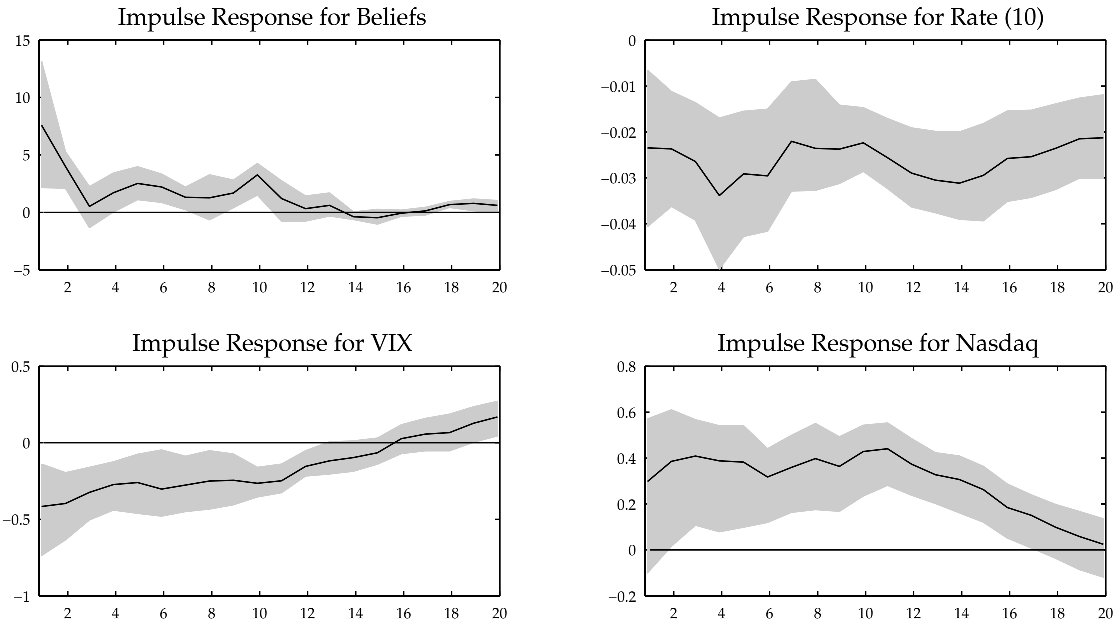

Figure 10: Impulse responses to shock to beliefs of late tapering: NASDAQ

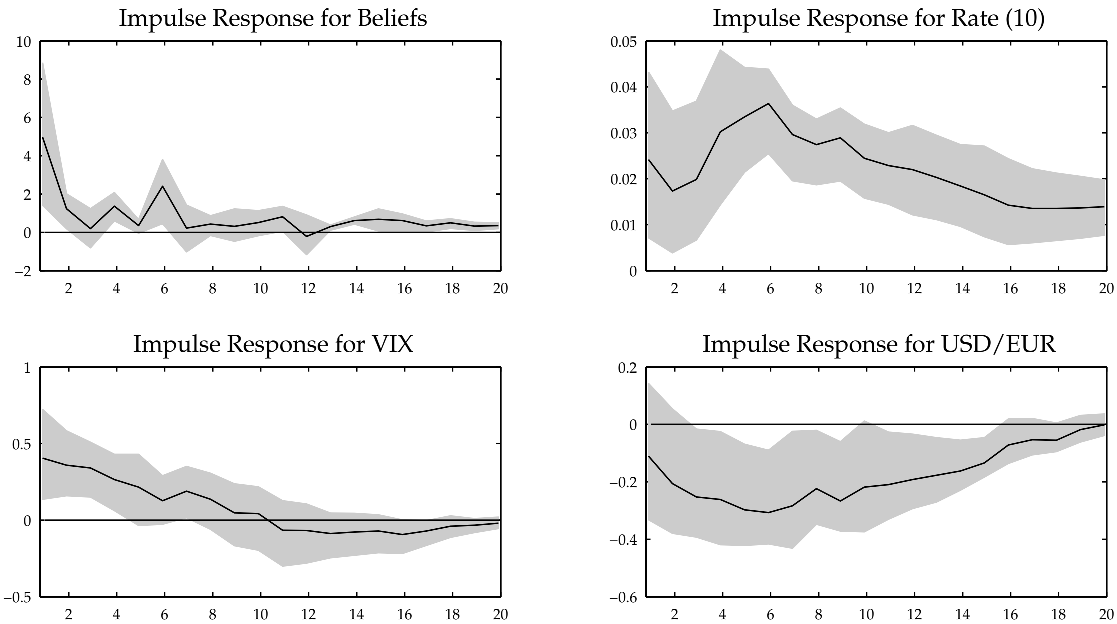

Figure 11: Impulse responses to shock to beliefs of early tapering: USD/EUR

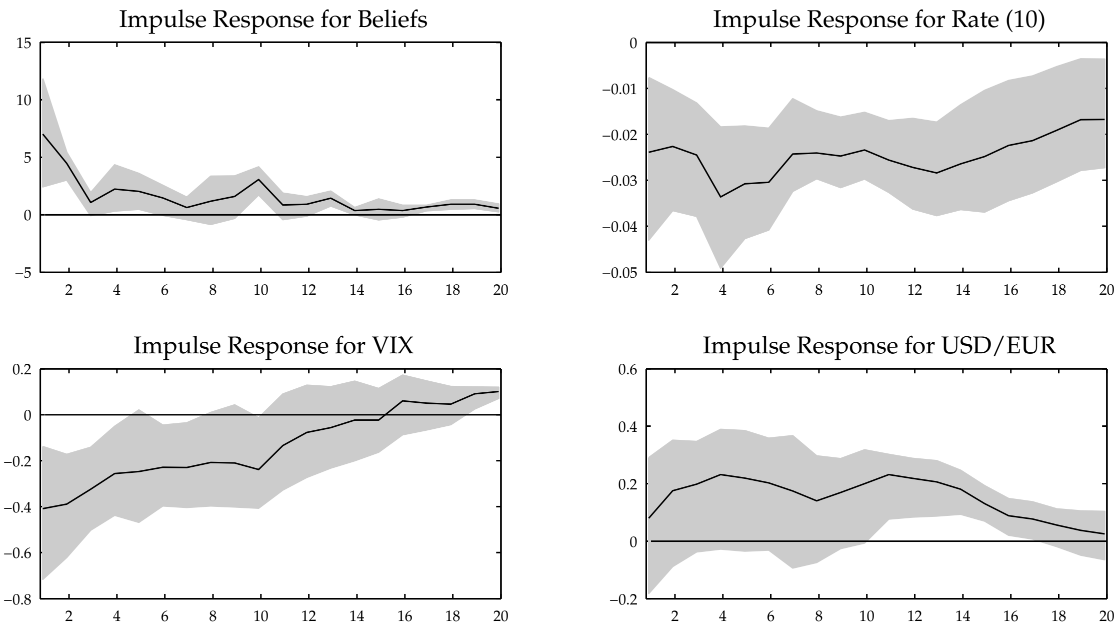

Figure 12: Impulse responses to shock to beliefs of late tapering: USD/EUR

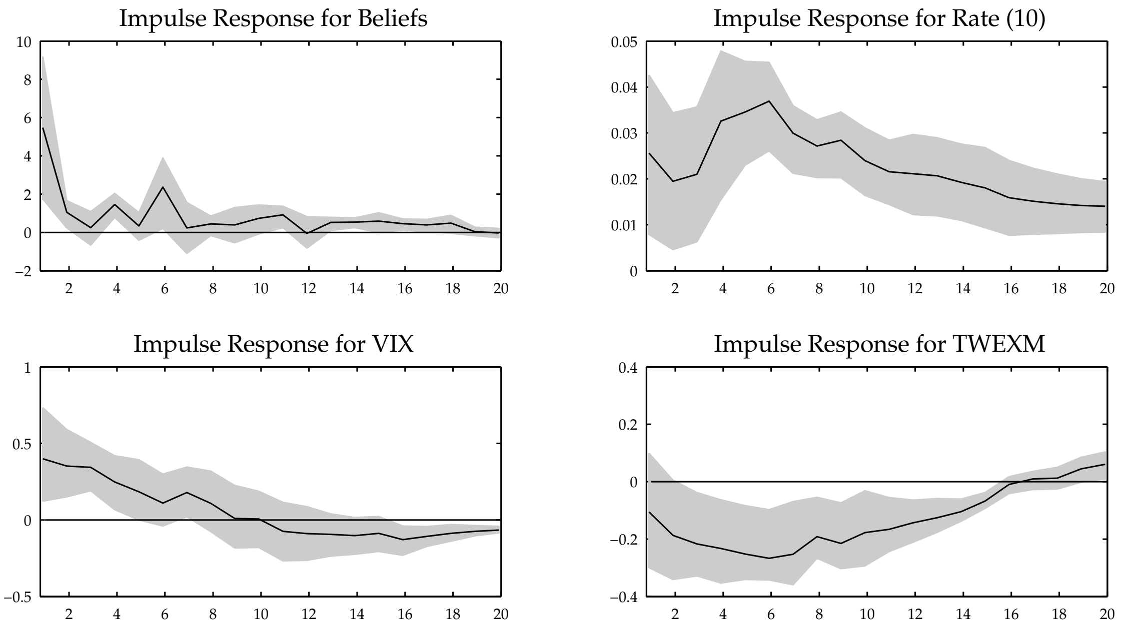

Figure 13: Impulse responses to shock to beliefs of early tapering: TWEXM

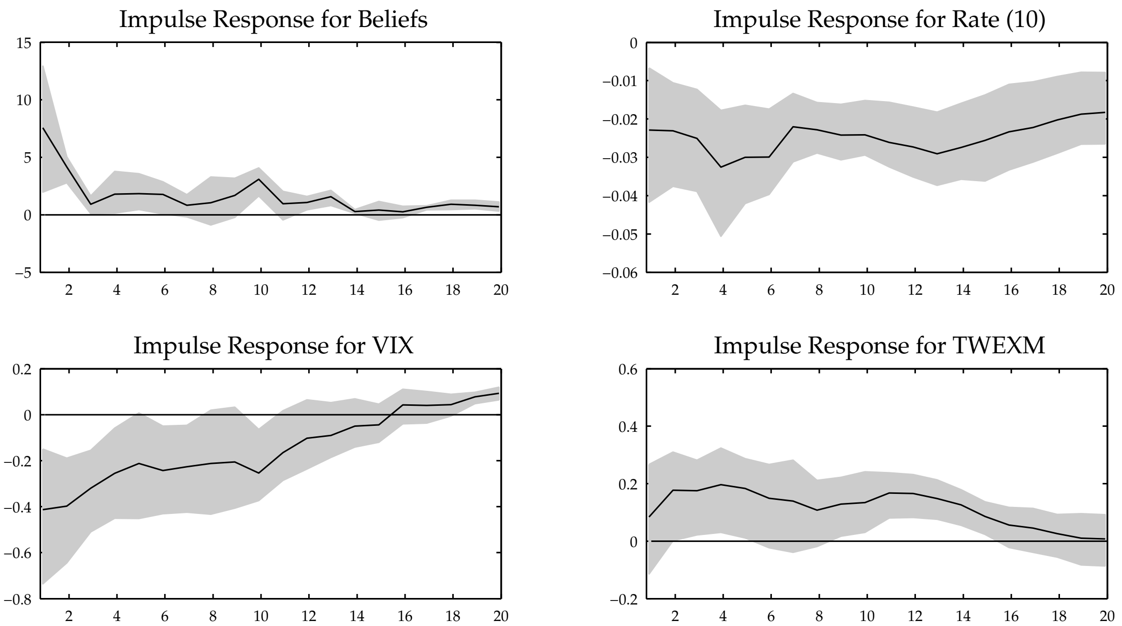

Figure 14: Impulse responses to shock to beliefs of late tapering: TWEXM

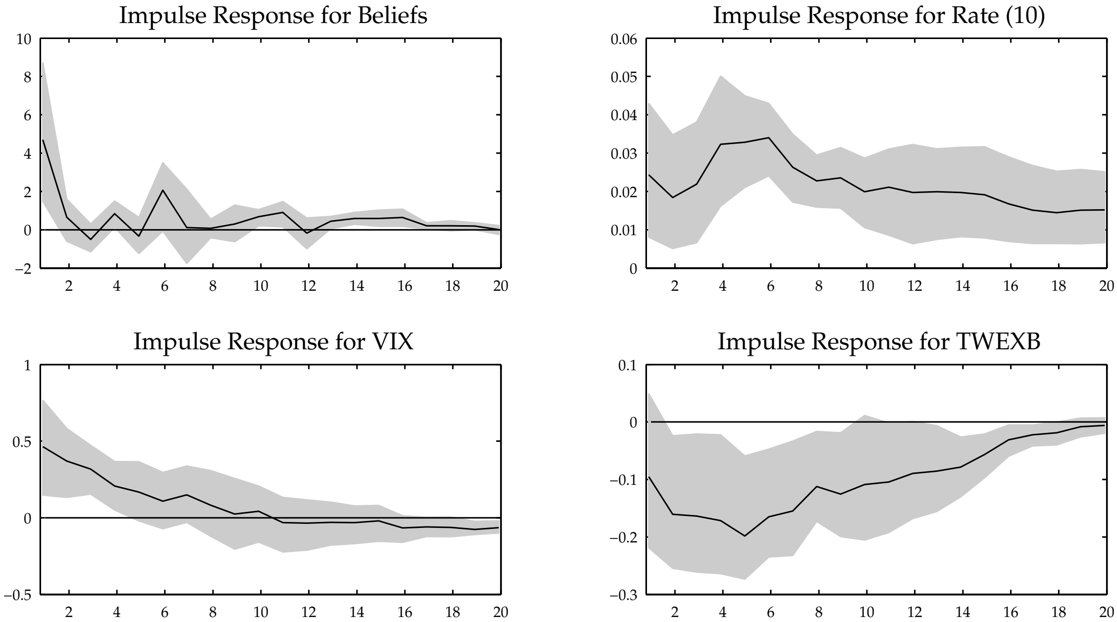

Figure 15: Impulse responses to shock to beliefs of early tapering: TWEXB

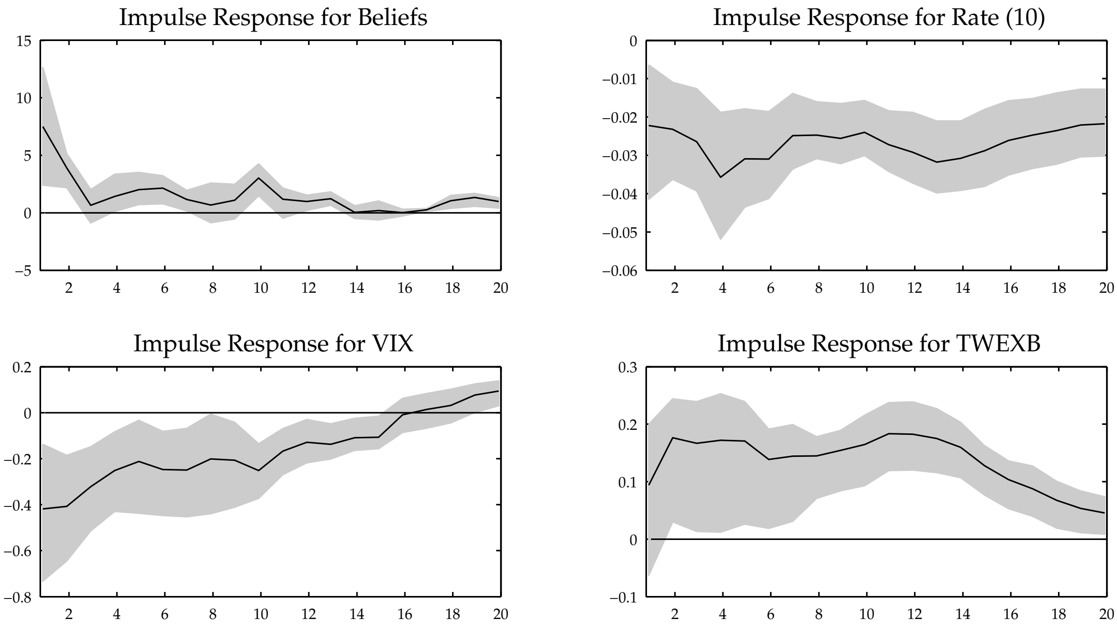

Figure 16: Impulse responses to shock to beliefs of late tapering: TWEXB

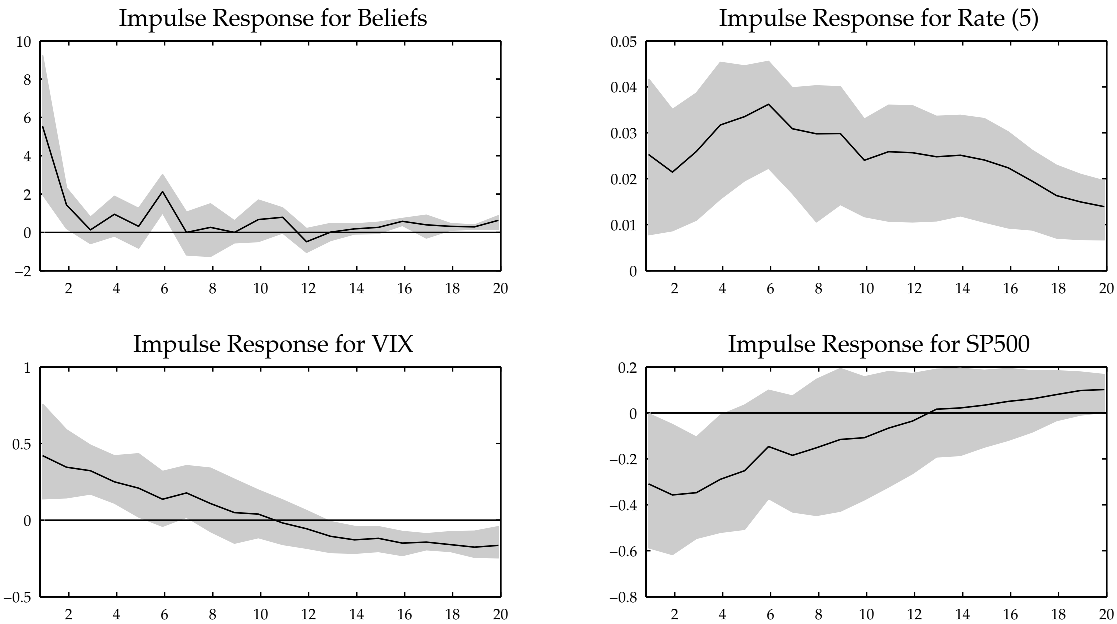

Figure 17: Impulse responses to shock to beliefs of early tapering: 5-year yield

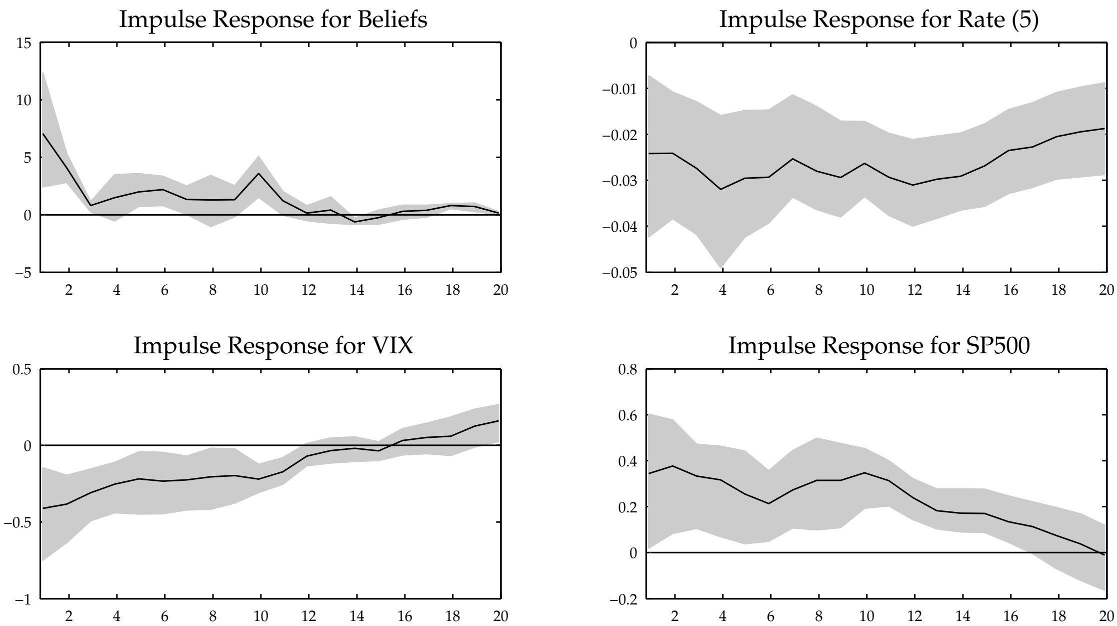

Figure 18: Impulse responses to shock to beliefs of late tapering: 5-year yield

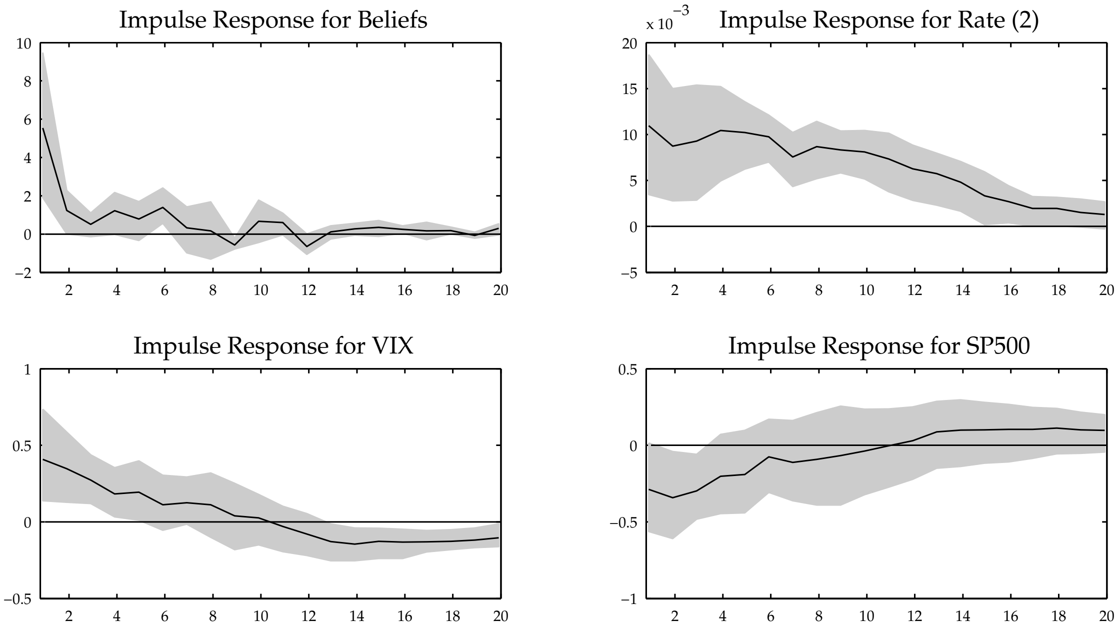

Figure 19: Impulse responses to shock to beliefs of early tapering: 2-year yield

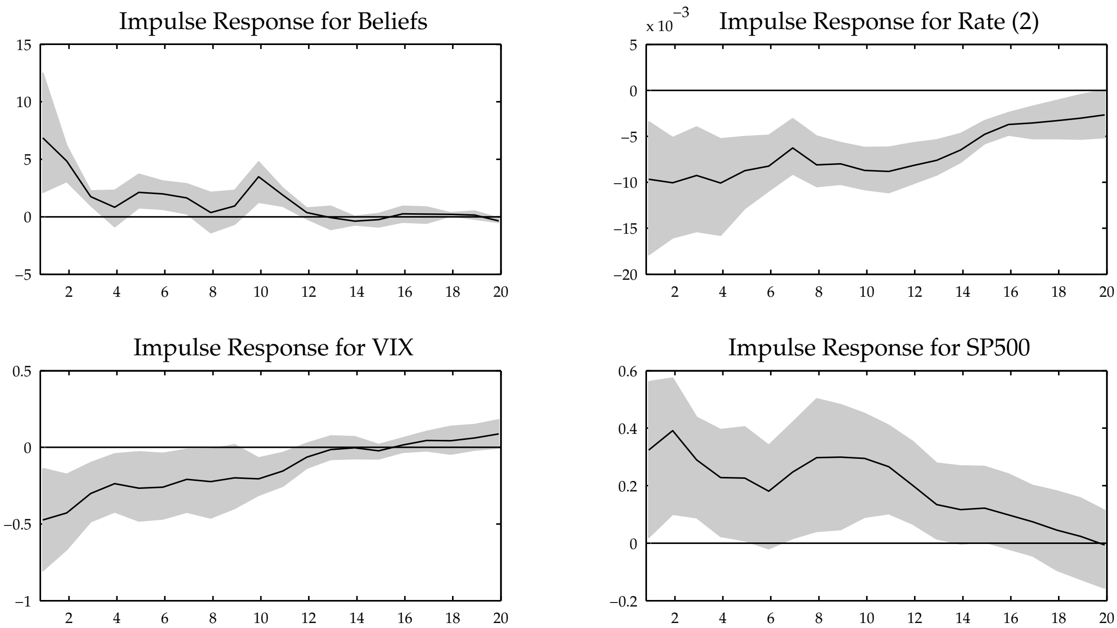

Figure 20: Impulse responses to shock to beliefs of late tapering: 2-year yield

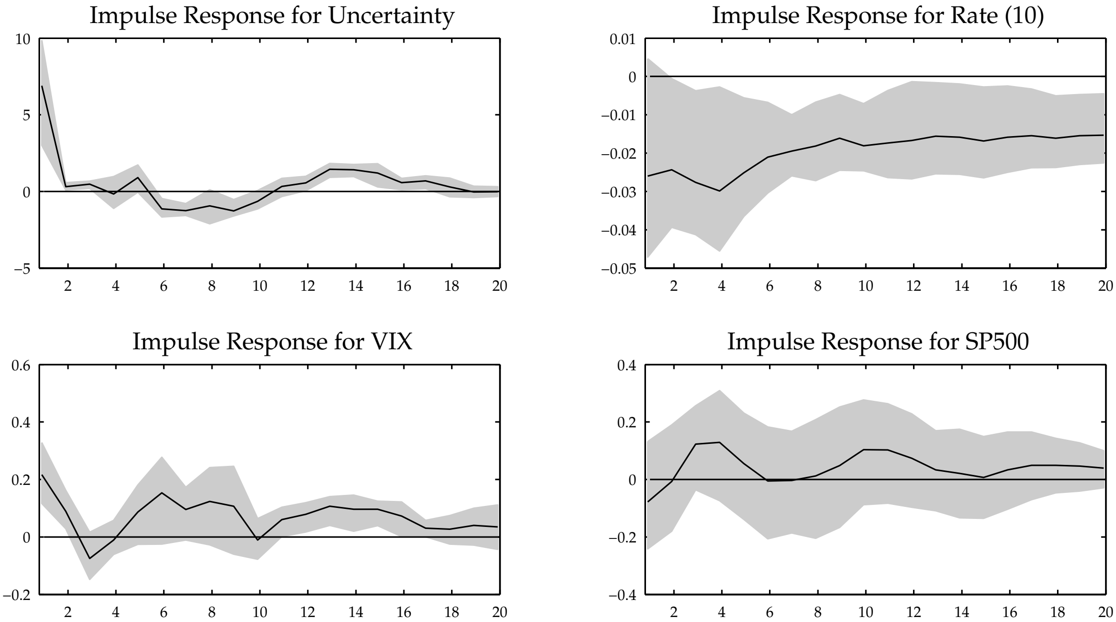

Figure 21: Impulse responses to shock to uncertainty: S&P500

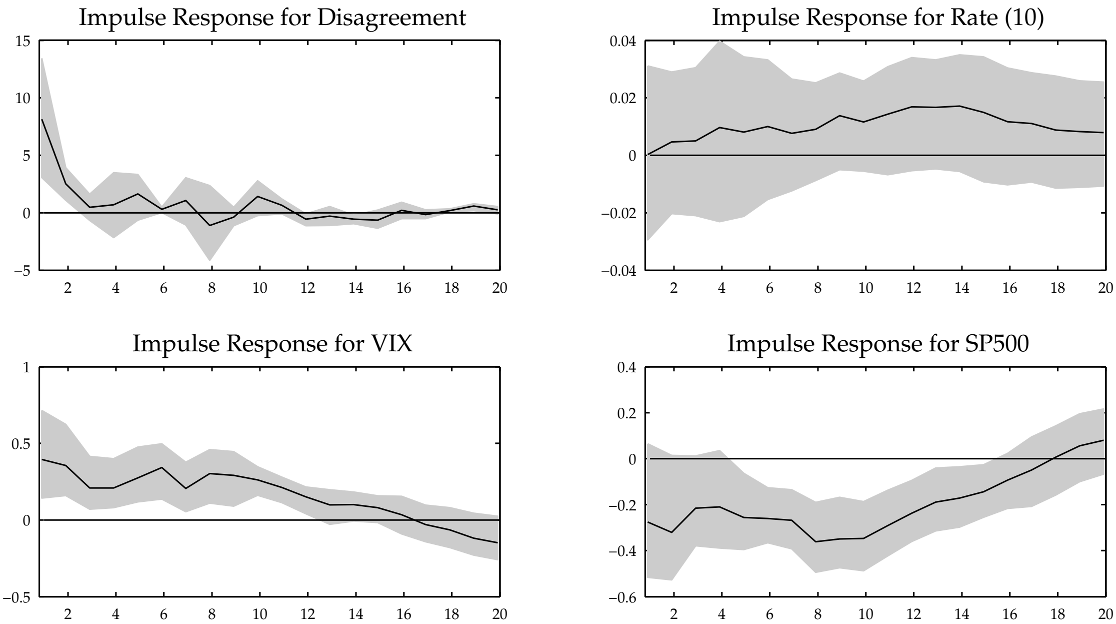

Figure 22: Impulse responses to shock to disagreement: S&P500

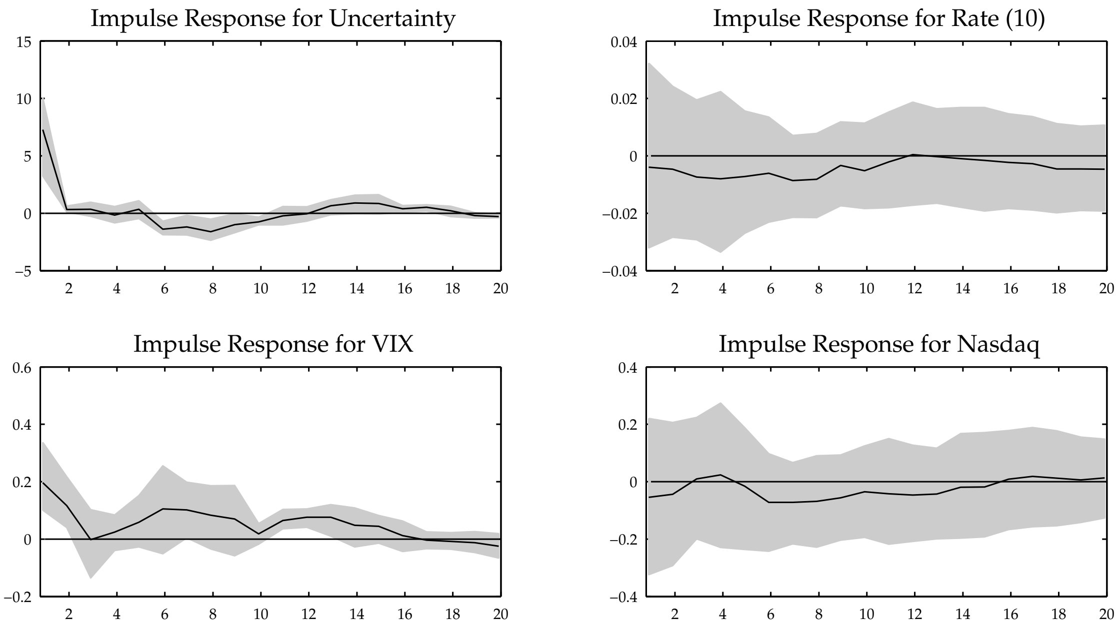

Figure 23: Impulse responses to shock to uncertainty: NASDAQ

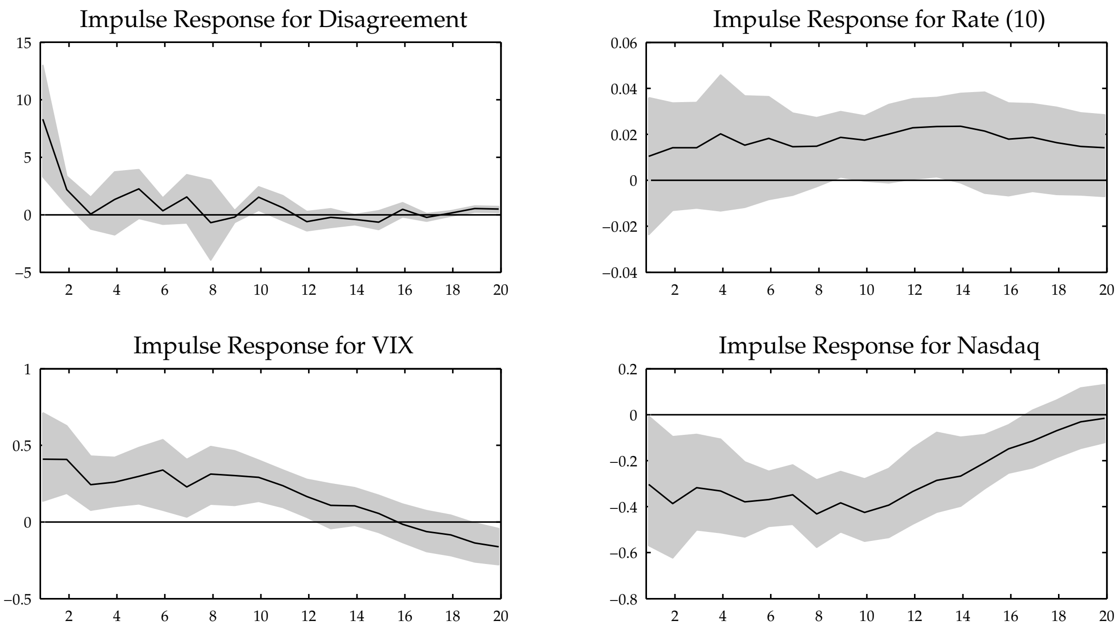

Figure 24: Impulse responses to shock to disagreement: NASDAQ

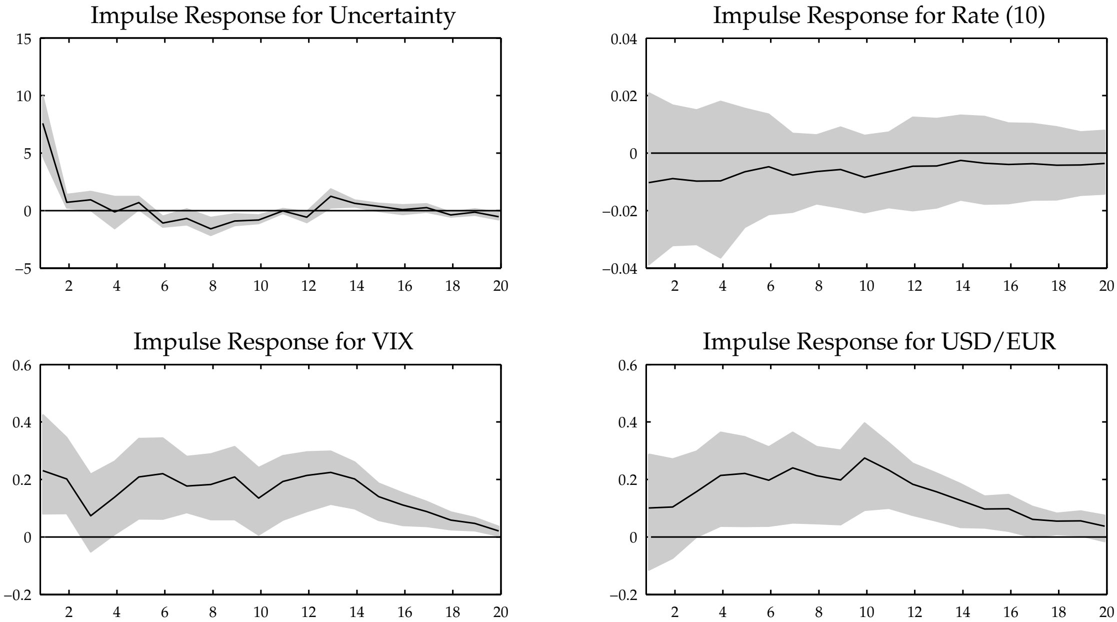

Figure 25: Impulse responses to shock to uncertainty: USD/EUR

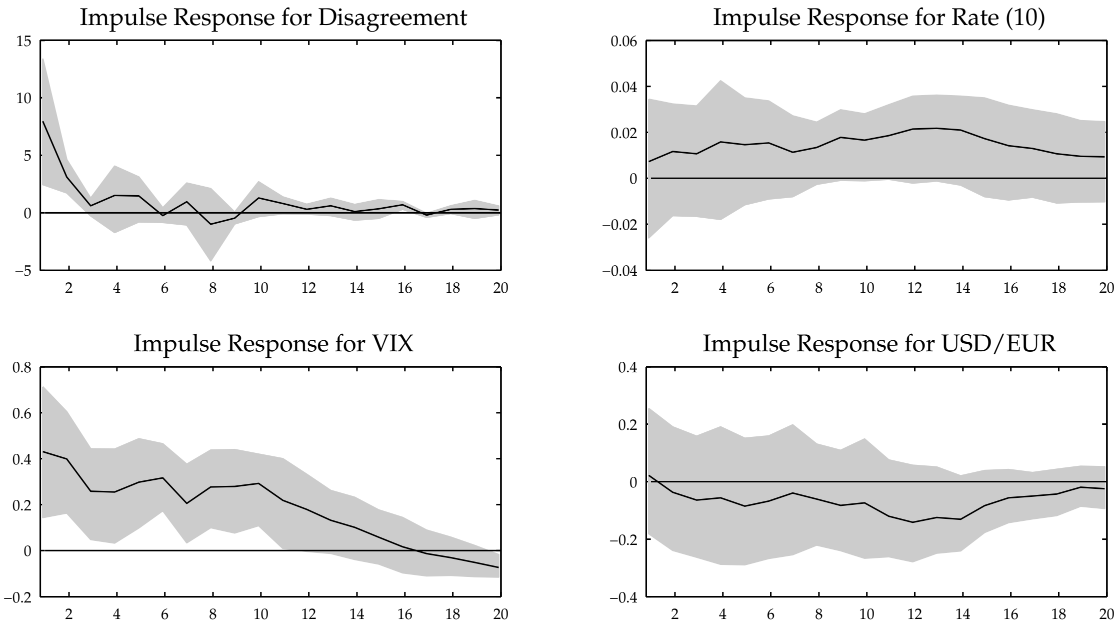

Figure 26: Impulse responses to shock to disagreement: USD/EUR

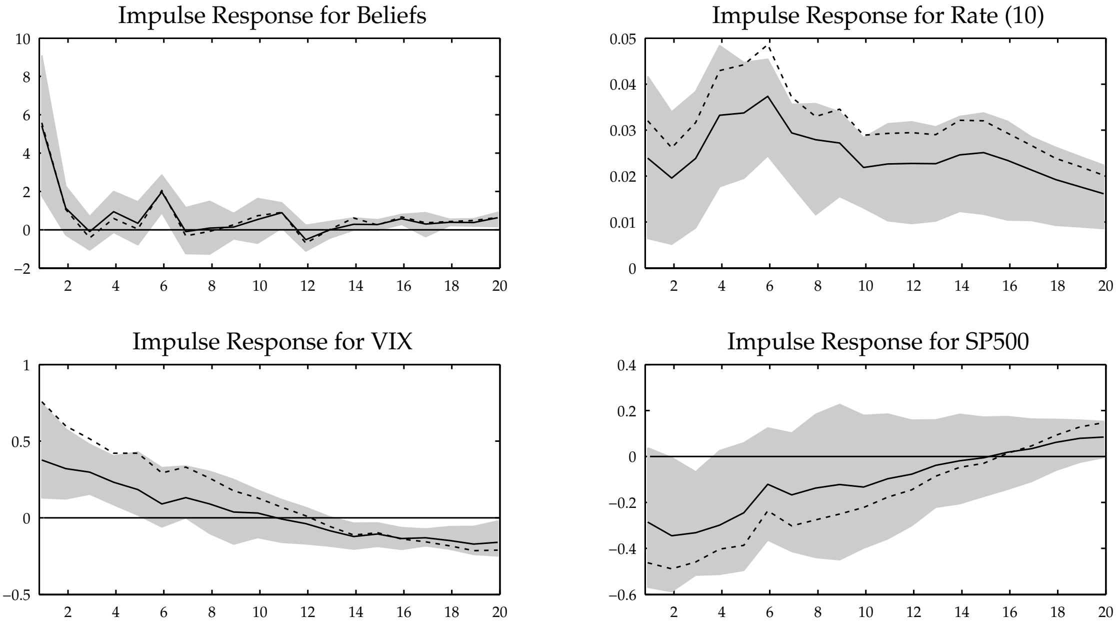

Figure 27: Impulse responses to shock in beliefs of early tapering: Fry/Pagan (2007)

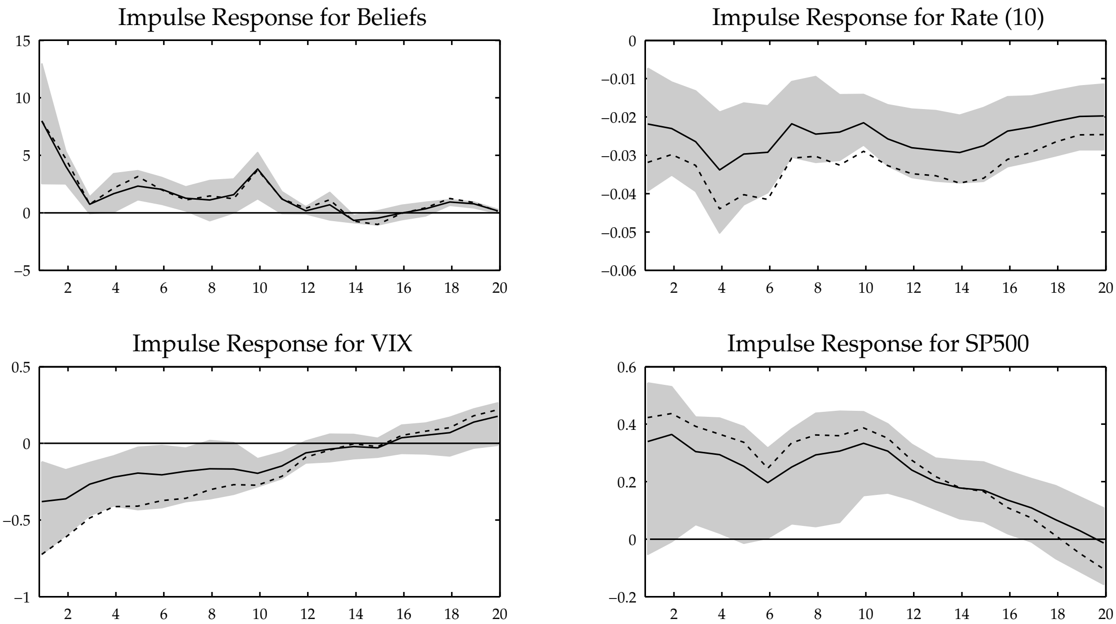

Figure 28: Impulse responses to shock in beliefs of late tapering: Fry/Pagan (2007)

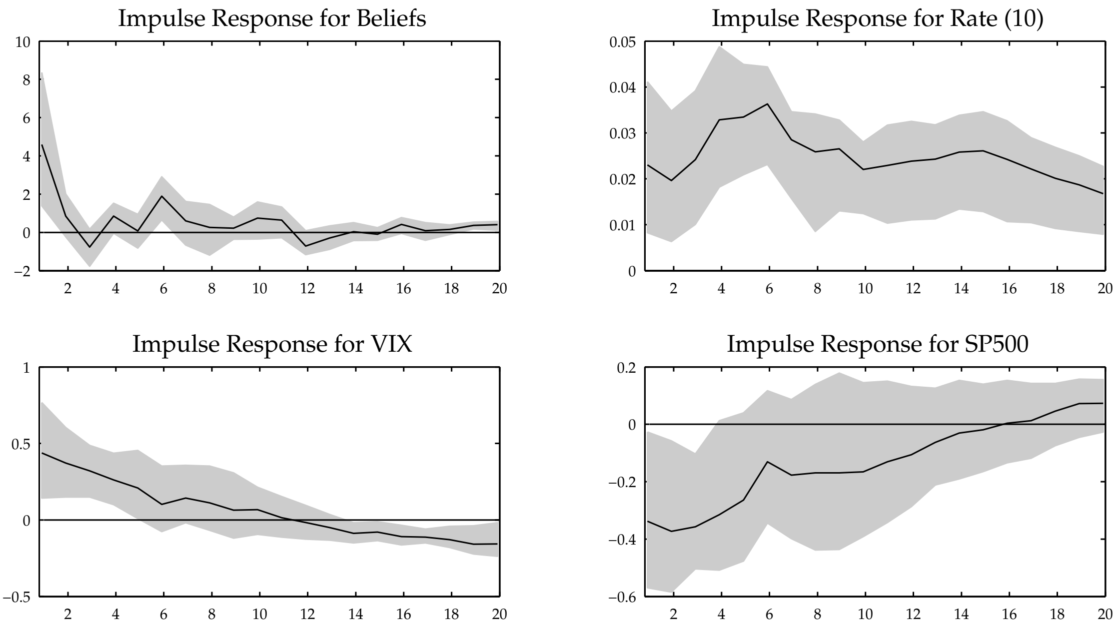

Figure 29: Impulse responses to shock in beliefs of early tapering: excluding retweets

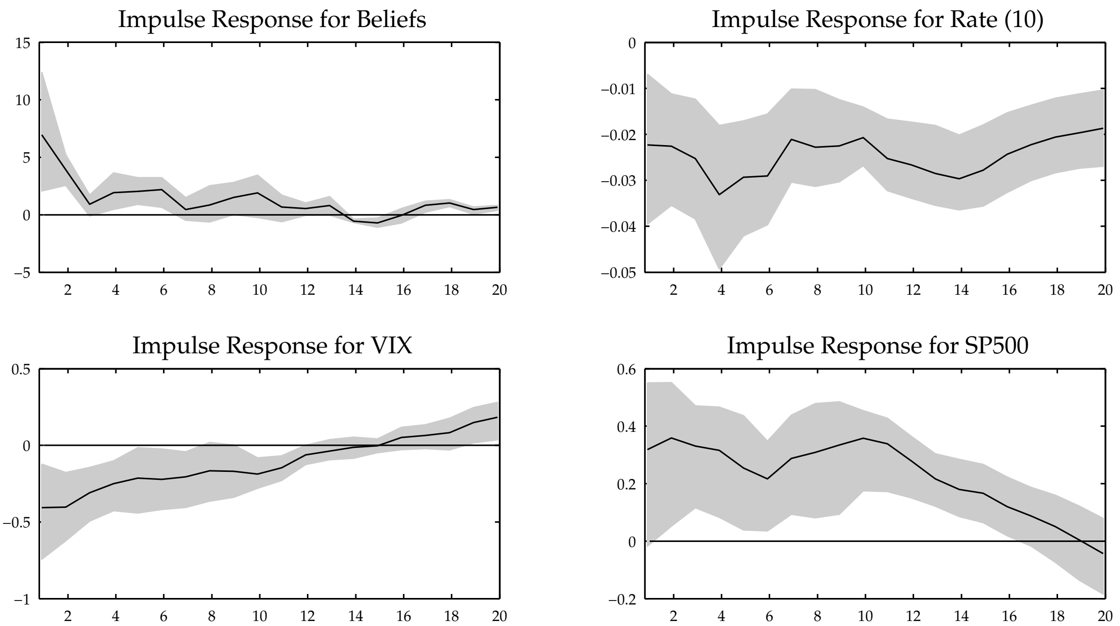

Figure 30: Impulse responses to shock in beliefs of late tapering: excluding retweets

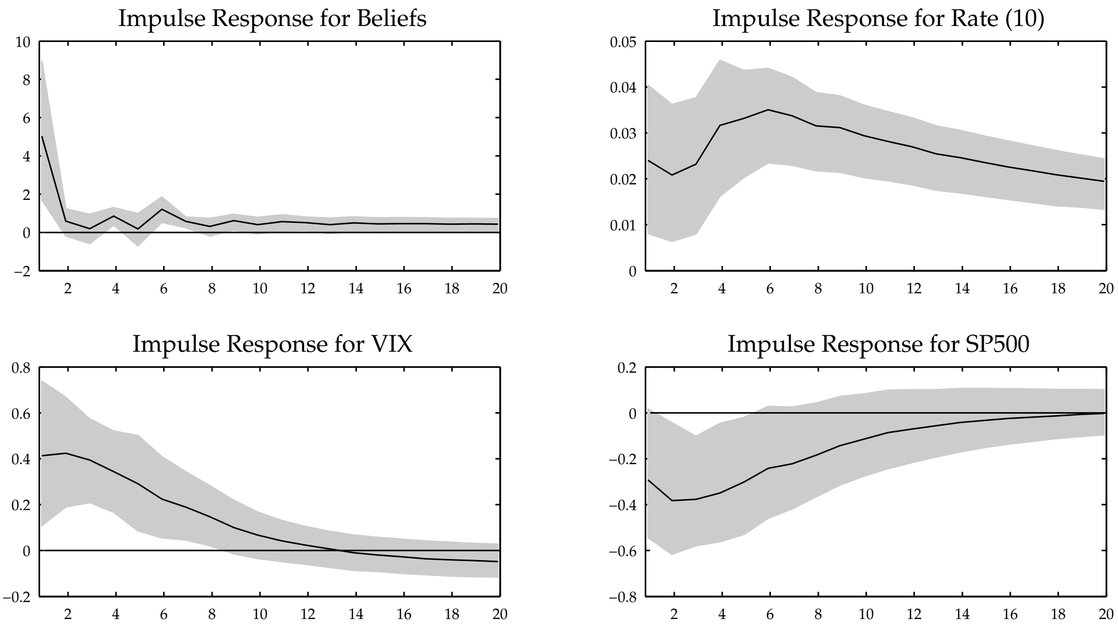

Figure 31: Impulse responses to shock in beliefs of early tapering: VAR(5)

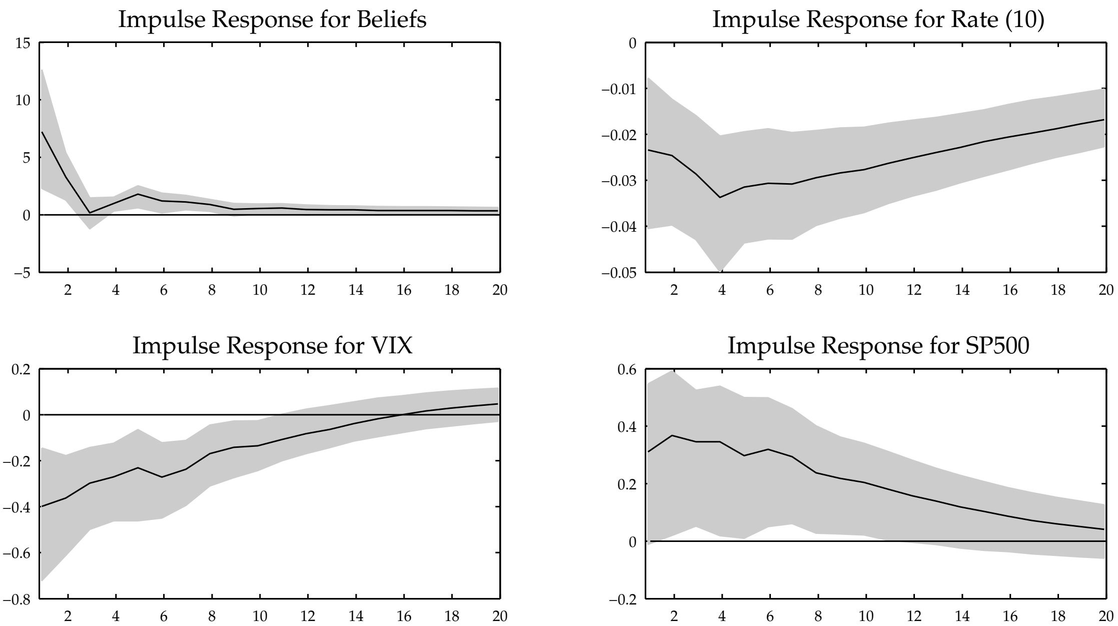

Figure 32: Impulse responses to shock in beliefs of late tapering: VAR(5)

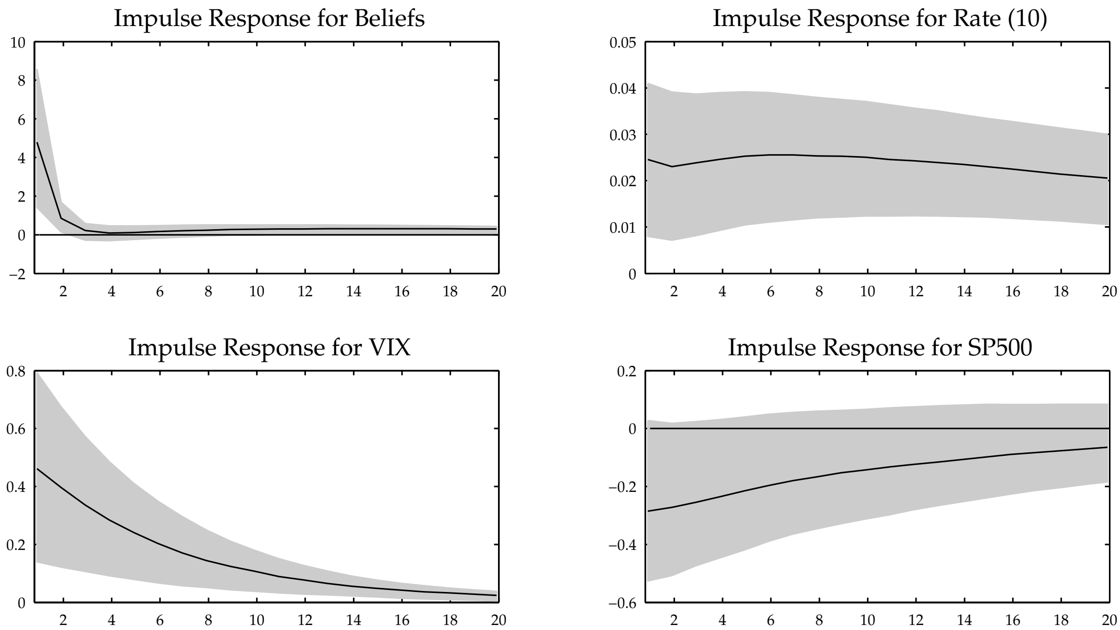

Figure 33: Impulse responses to shock in beliefs of early tapering: VAR(1)

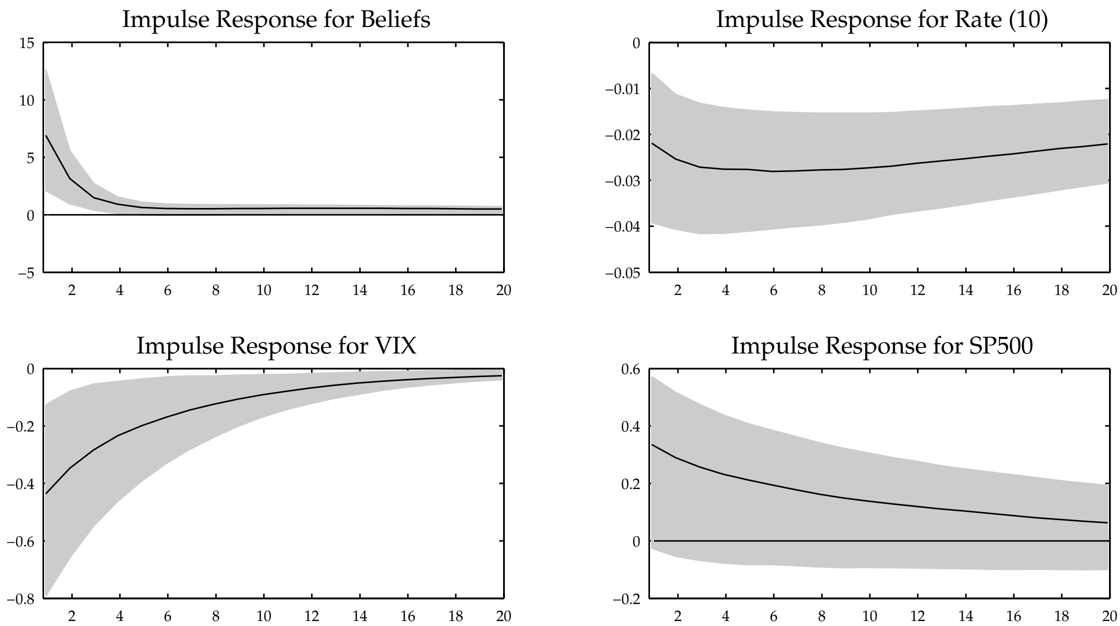

Figure 34: Impulse responses to shock in beliefs of late tapering: VAR(1)

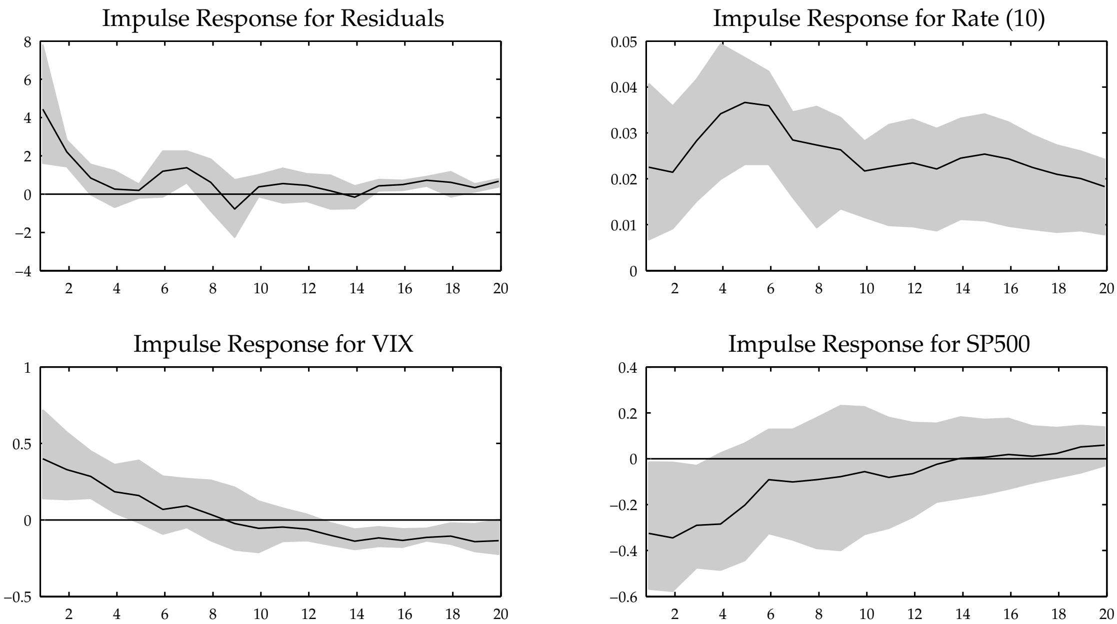

Figure 35: Impulse responses to shock in (residual) beliefs of early tapering

Table 5: Forecast error variance decomposition

variable	impact of belief shock (in % of total variation)					
	tapering soon			**tapering late**		
	at horizon			at horizon		
	1 day	10 day	20 day	1 day	10 day	20 day
$Rate_t$	14.66	18.00	18.30	14.40	18.51	18.76
VIX_t	15.98	18.46	19.02	16.81	19.68	19.84
$Asset_t$	17.17	19.44	19.56	17.20	20.50	20.62

variable	impact of belief shock (in % of total variation)					
	uncertainty			**disagreement**		
	at horizon			at horizon		
	1 day	10 day	20 day	1 day	10 day	20 day
$Rate_t$	11.79	15.11	18.51	15.82	15.43	16.46
VIX_t	11.05	15.17	18.60	19.29	18.47	18.76
$AssetP_t$	11.20	15.71	19.79	19.57	18.55	19.13