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Quantitative Easing and Tapering Uncertainty: Evidence from Twitter

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Quantitative Easing and Tapering Uncertainty: Evidence from Twitter

February 20, 2015

Abstract

In this paper we analyze the effects of changes in peoples' beliefs about the timing of the exit from Quantitative Easing ("tapering") on asset prices. To quantify beliefs of market participants, we use data from Twitter, the social media application, covering 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 strong and robust 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 emerging literature on macroeconomic uncertainty shocks.

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

JEL classification: E32, E44, E52

1 Introduction

After 2008 the U.S. Federal Reserve adopted a series of unconventional monetary policy measures in order to enhance credit conditions and support the economic recovery. Large-scale asset purchases known as Quantitative Easing (QE) led to a tripling of the Fed's balance sheet.¹ When then-Federal Reserve Chairman Ben Bernanke on May 22 2013 for the first time mentioned the possibility of reducing asset purchases while testifying to the U.S. Congress, markets were wrong-footed.² 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 severe appreciation of the US dollar, in particular 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."³

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

²In addition, on May 22 the minutes of the April/May FOMC meeting were published.

³In 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

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. In particular, we aim at, first, quantifying the response of interest rates, exchange rates and other asset prices to shocks to the tapering beliefs of market participants. Second, we decompose the dynamics of asset prices in order to isolate the fraction of movements due to changes in tapering beliefs. Third, we derive a measure of monetary policy uncertainty from Twitter contributions as well as a measure of disagreement of market participants about future monetary policy and quantify their effects on financial variables.

The main problem 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 available on a very low frequency only, 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 to extract measures of disagreement of market participants. In this paper, we offer a new approach to identify shocks to peoples' beliefs about policy based on the advantages of social media. We use data from Twitter, the popular application for short text messages ("tweets") of at most 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) tweets reflect personal views of market participants and (2) 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 allows us to identify belief shocks and their dynamic effects. In 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

of expectations. In the July survey, market professionals were expecting purchases of only 65 billion dollars at the September FOMC meeting and only 50 billion dollars after the December meeting.

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.

Understanding market responses to exiting from QE matters. Not only is the Fed about to gradually exit from unconventional monetary policy, but also the Bank of England and, at some point in the future, also the Bank of Japan and the European Central Bank. Communicating the exit from unconventional monetary policy to financial markets and the public is essential for a smooth and frictionless return to normal. Data from social media is a useful cross-check 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 as follows: Section two briefly reviews the related literature. Section three introduces our data set on Twitter messages, which is used for the empirical analysis in section four. The results are discussed in section five. After a section devoted to the analysis of extensions and the robustness of our results, section six, section seven concludes and draws some policy implications.

2 The literature on Fed tapering and uncertainty shocks

This paper is related to several strands of the literature. First, there are a few papers on the impact of tapering announcements 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 testimony. She finds that the strength of emerging markets' responses reflects internal and external weaknesses.

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 meeting and, in particular, mounting uncertainty before FOMC meeting, which cannot be appropriately be 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 Vasishta (2014) identify a "policy normalization shock" 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.

Second, and more generally, our paper adds to the booming literature of uncertainty shocks and the macroeconomic consequences. Over recent years researchers build indicators of uncertainty and put them into VAR models. This literature was started

by 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 from newspaper references to uncertainty and show that this index has predictive power for several macroeconomic variables.⁴ On a business-level, Bachmann et al. (2013) use German survey data in a VAR model. They find that higher uncertainty of businesses contributes 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. The usage of Twitter is progressively 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 136 countries and the exact time they were sent.⁵ 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, at which the Fed eventually decided not yet to taper QE. The sample period covers the entire "taper tantrum" episode and is sufficiently long to perform a VAR analysis. Further,

⁴An alternative to utilizing survey data or news reports is offered by Caldara et al. (2014). They derive uncertainty shocks from a penalty function approach.

⁵Retweets 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.

the data set comprises each tweet's text message of at most 140 characters, the name of the Twitter user and her location.

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 a small number of active users that share their opinions about the Fed's future policy stance frequently and a large number of users that generate tweets about Fed tapering rather infrequently. Excluding retweets does not change the distributional properties of the data.

In order to contribute along several dimensions the tweets are then separated into 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 gives 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 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 soon. 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 surrounding FOMC meetings. We count a total of 7687 tweets referring to sooner tapering and nearly twice as much i.e., 14.555 tweets that are associated with later tapering. 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 $Tweets_t^{late}$, are positively correlated with a correlation coefficient of 0.4 and peak both on September 18, 2013, while the FOMC September meeting was held, 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 and a late tapering could increase at the same day, i.e., there is substantial heterogeneity in market participants' beliefs about future policy. This property motivates us to construct two additional indicators reflecting the uncertainty and the disagreement of market commentators, respectively, about future policy. The uncertainty indicator, $Tweets_t^{uncertain}$, 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 $i = \{soon, late, uncertain\}$.

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 both 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 sooner tapering is equally big as the fraction of beliefs referring to later tapering. Whereas if both fractions diverge i.e, one opinion concerning the future monetary policy stance dominates the other, 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, i.e. unexpected changes in their views about the Fed’s propensity to taper. Our estimation strategy is to put the series of tweets extracted before into a standard VAR model alongside 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 $B(L) \equiv B_0 - B_1L - B_2L^2 - \dots - B_pL^p$ 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 $A(L) \equiv I - A_1L - A_2L^2 - \dots - A_pL^p$ 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

$$Y_t = (\textit{Beliefs}_t^j, \textit{Rate}_t, \textit{VIX}_t, \textit{AssetP}_t)'$$

where $\textit{Beliefs}_t^j$ with $j = \{\textit{soon}, \textit{late}, \textit{uncertain}, \textit{disagreement}\}$ reflects tapering belief proxies, \textit{Rate}_t stands for the 10-year, 5-year or 2-year, respectively, constant maturity Treasury bill rate, \textit{VIX}_t is the index of implied stock market volatility which is typically used as a proxy for risk aversion and \textit{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.⁶

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.

4.2 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 very useful alternative to identify a structural shock in this VAR analysis.⁷ 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 in using sign-restrictions our VAR is best suited to deal with the mutual interaction among market beliefs about policy, asset prices and volatility indicators even though most of the literature on uncertainty shocks reviewed before such as Bloom (2009) and Baker et al. (2013), rely on triangular identification schemes instead.

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

⁶All data is taken from the FRED database of the St. Louis Fed.

⁷Recently, Gambacorta et al. (2014) also used sign restrictions to identify an unconventional monetary policy shock in a panel VAR study.

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 or our measures of uncertainty and disagreement.

Table 1: Sign restrictions to identify a belief shock

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

The belief shock is identified by imposing positive responses of $Beliefs_t^i$ 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 to a depreciation of foreign currencies against the USD.⁸ 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 our 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

⁸Since 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.

shock. Additionally, we show the 16th and 84th percentiles of all accepted impulse responses.

5.1 Shocks to tapering beliefs

Our benchmark results are presented in Figures (7) to (20) which are reflecting 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 4 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. Thus, a shift in beliefs of an early tapering of 5% 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 onto the adjustment dynamics. The resulting adjustment is typically not completed after the 20-day horizon depicted here.

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 reactions is statistically significant only for one day. With a drop by 0.4%, stock prices appear very sensitive to tapering beliefs.

A key feature of our Twitter data set is that we can use the heterogeneity of users' beliefs. 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 a "tapering late" belief shock.. Market volatility and the long-term interest rate decrease. However, it can be seen from Figure (8) that now a "tapering late" belief shock induces a persistent positive response of the S&P 500. Broadly speaking, the responses to a shock to early or late tapering beliefs appear symmetric, with a slight tendency for asset prices to respond more significantly to "late tapering" beliefs.

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 instantly 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 speedy 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 a 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 as such. 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 Leduc and Liu (2012), while a shock to the disagreement index shows no effect on the interest rate. Nevertheless, asset prices fall significantly in the medium-term when the disagreement of market participants increases.

In a VAR setting in which the S&P 500 stock market index is replaced by the NASDAQ Composite that mainly tracks technology stocks our results remain nearly unchanged both in terms of the dynamics and the 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 by 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 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. 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 (2). 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 and, finally, we will estimate an alternative model specification. 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 aim to check the robustness of our findings for 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 main results remain untouched. It can be seen that the dynamic effects of a belief shock are maintained while solely the magnitude of all responses increases noticeable. Our results presented before can be

interpreted as a conservative estimate of the effects of belief shocks. However, we will proceed our robustness analysis by focusing on the median responses only.

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 robust regarding the exclusion of 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.

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. This is additional evidence for QE having the intended expansionary effects in the first place.

Second, we showed 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, for which we showed that beliefs of an early and a late tapering could increase 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 importance of 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 for other central banks to avoid exceptional market volatility.

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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 large set of Twitter messages.

[To be completed.]

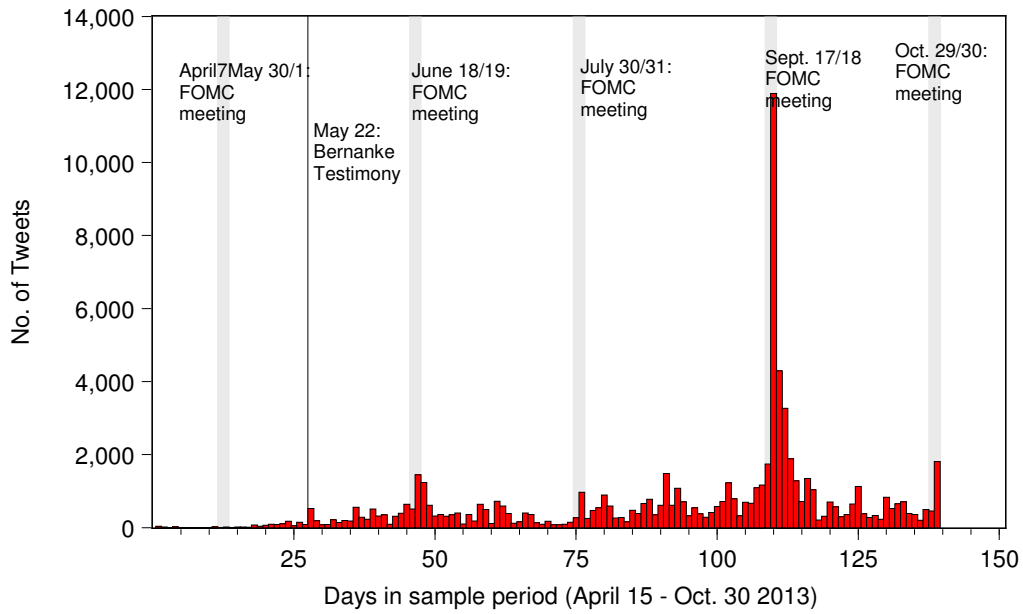


Figure 1: All tweets containing "Fed" and "Taper"

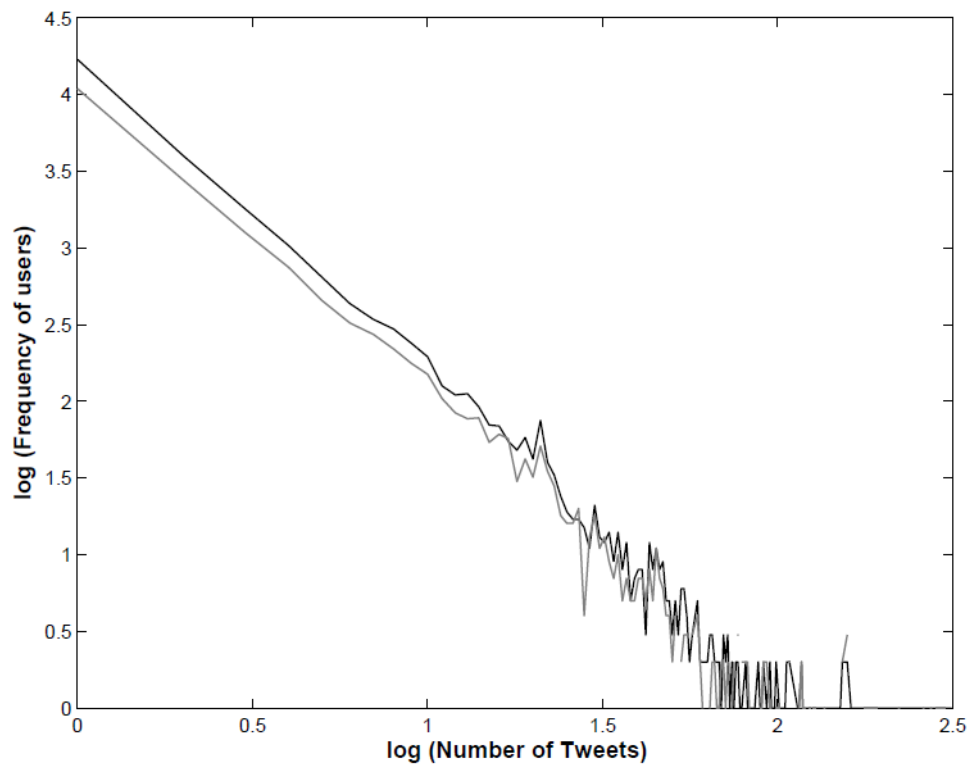


Figure 2: Distribution of all tweets (black) and all tweets excluding retweets (grey) and users in log scale

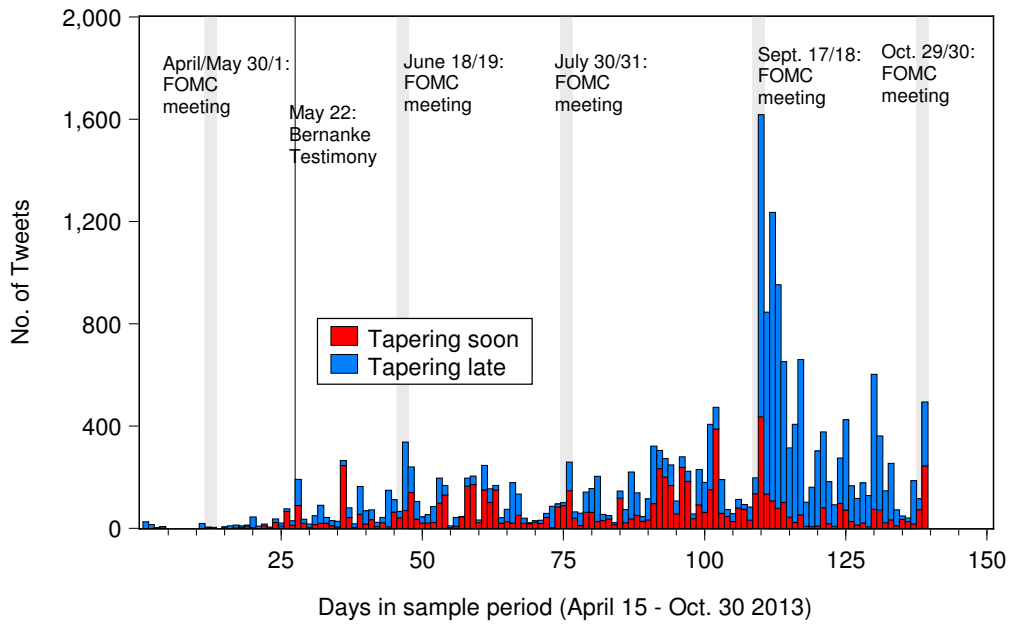


Figure 3: Tweets expressing beliefs on soon/late tapering

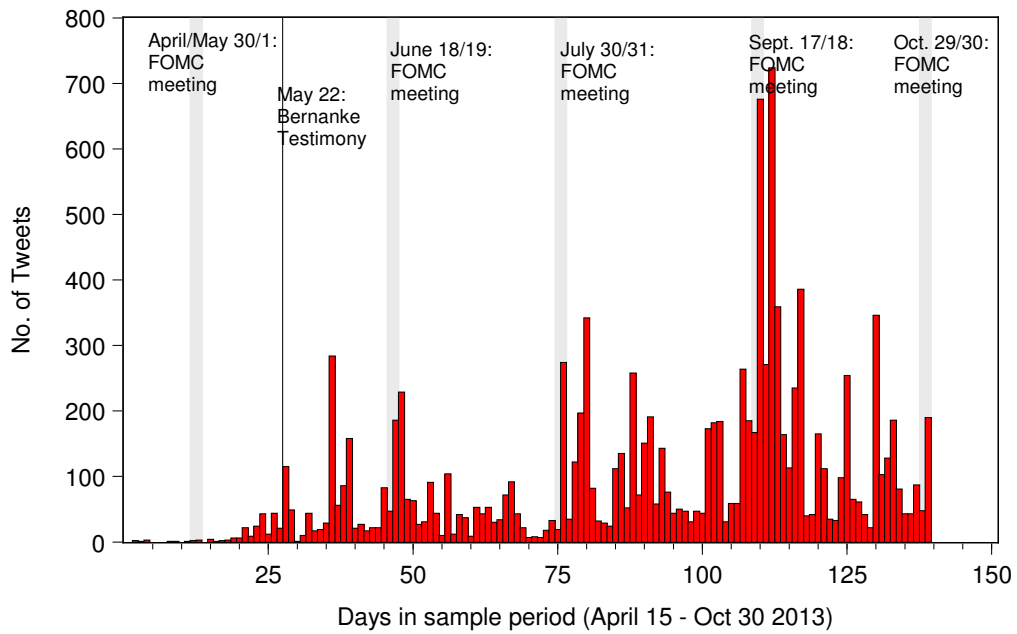


Figure 4: Tweets expressing uncertainty about tapering



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

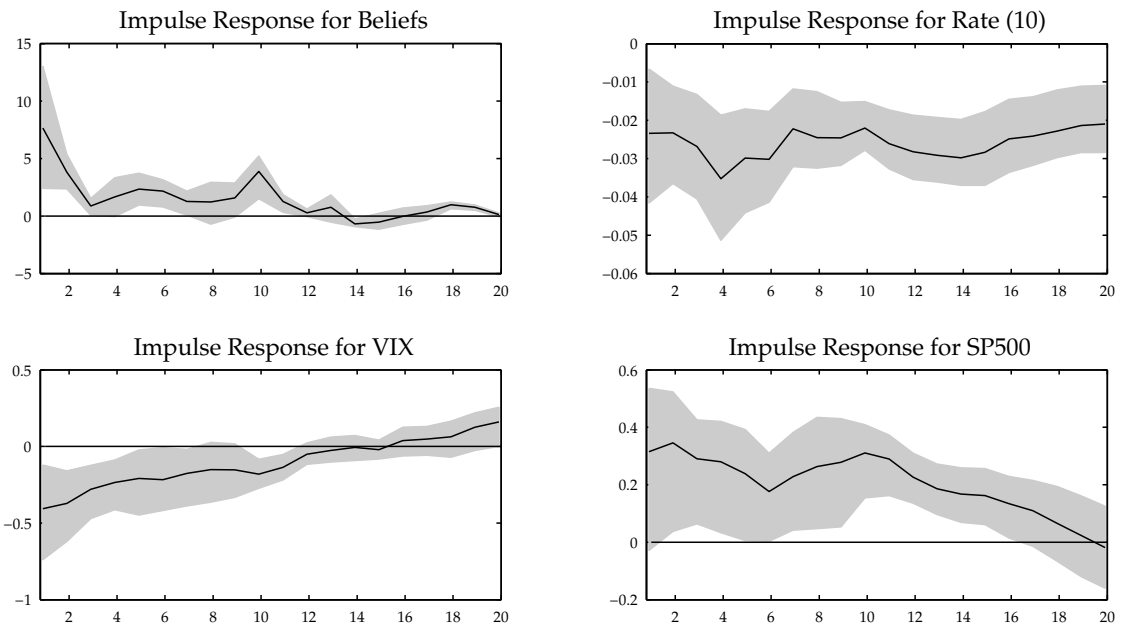


Figure 8: Impulse responses to shock to beliefs of late tapering: S&P500

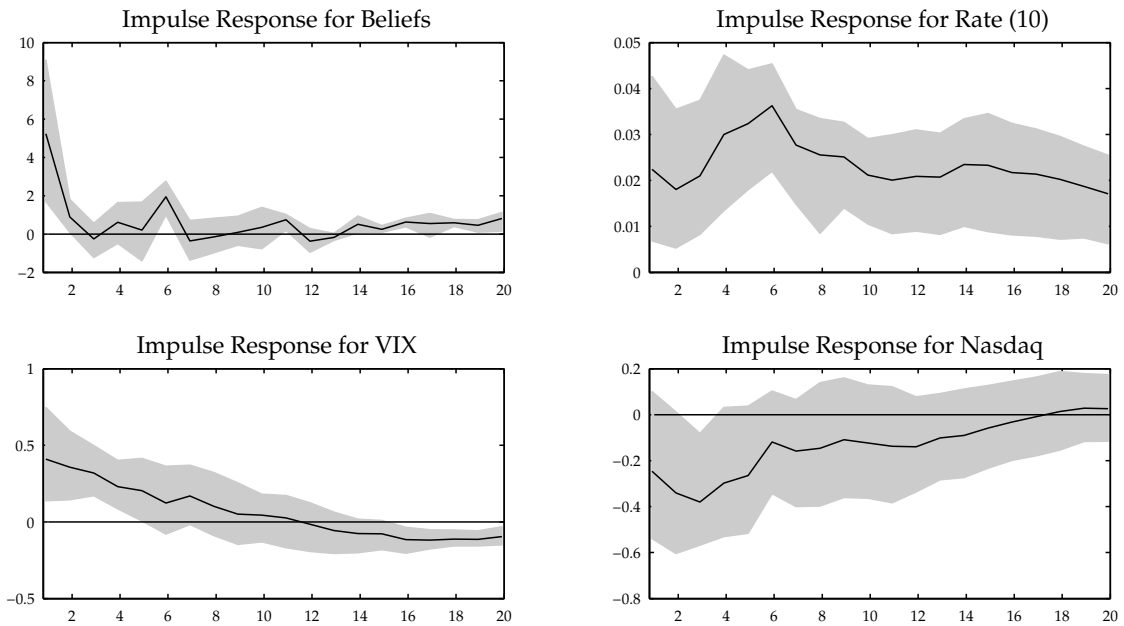


Figure 9: Impulse responses to shock to beliefs of early tapering: NASDAQ

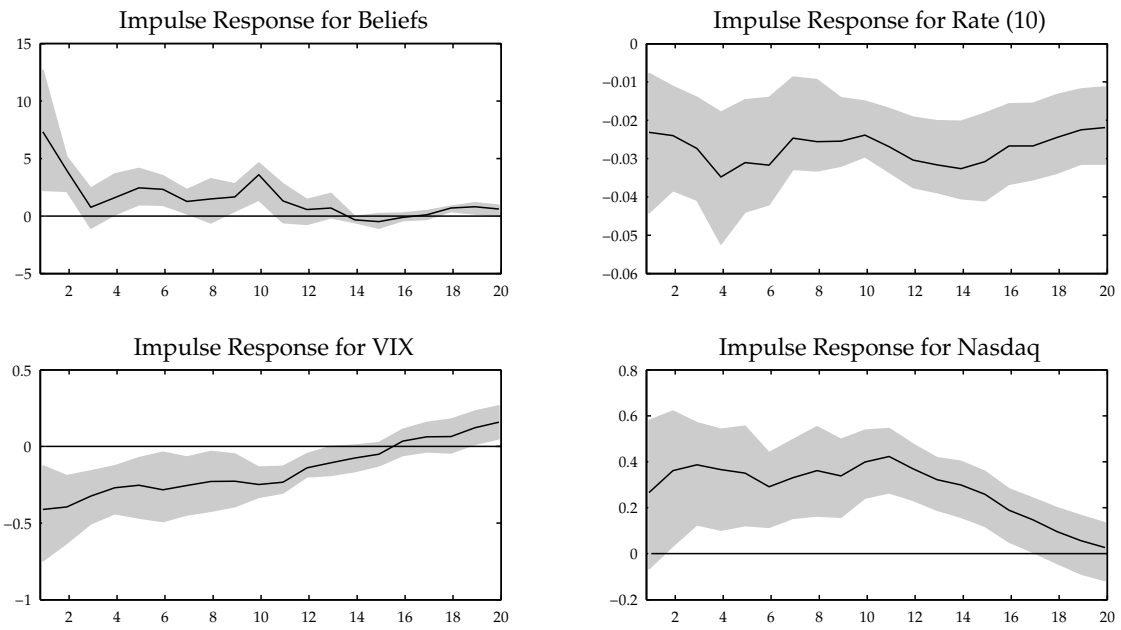


Figure 10: Impulse responses to shock to beliefs of late tapering: NASDAQ

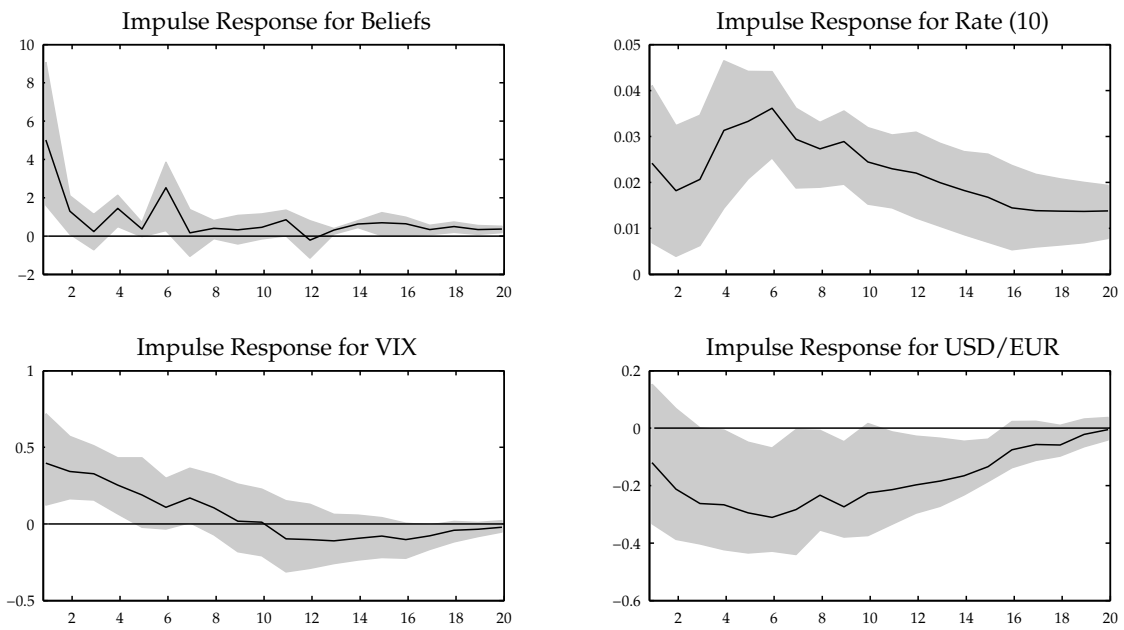


Figure 11: Impulse responses to shock to beliefs of early tapering: USD/EUR

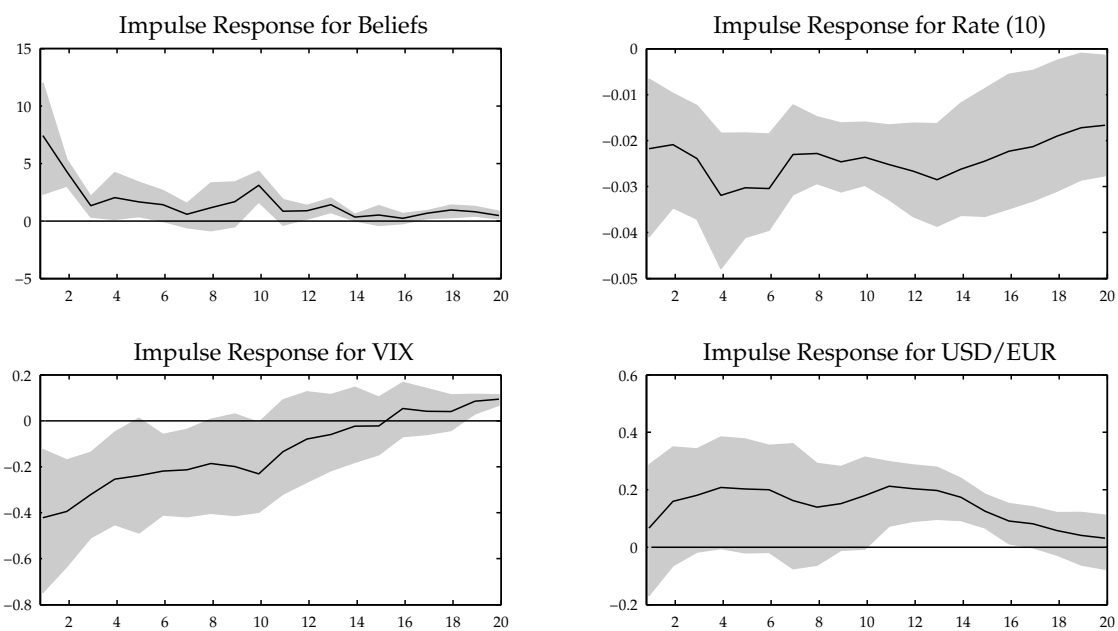


Figure 12: Impulse responses to shock to beliefs of late tapering: USD/EUR

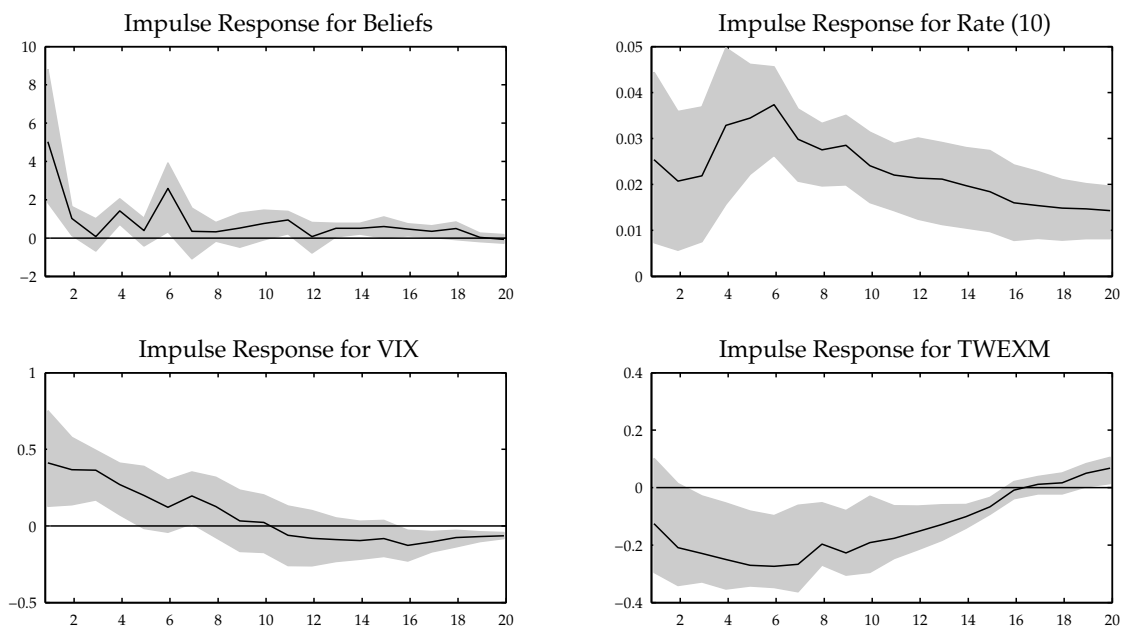


Figure 13: Impulse responses to shock to beliefs of early tapering: TWEXM

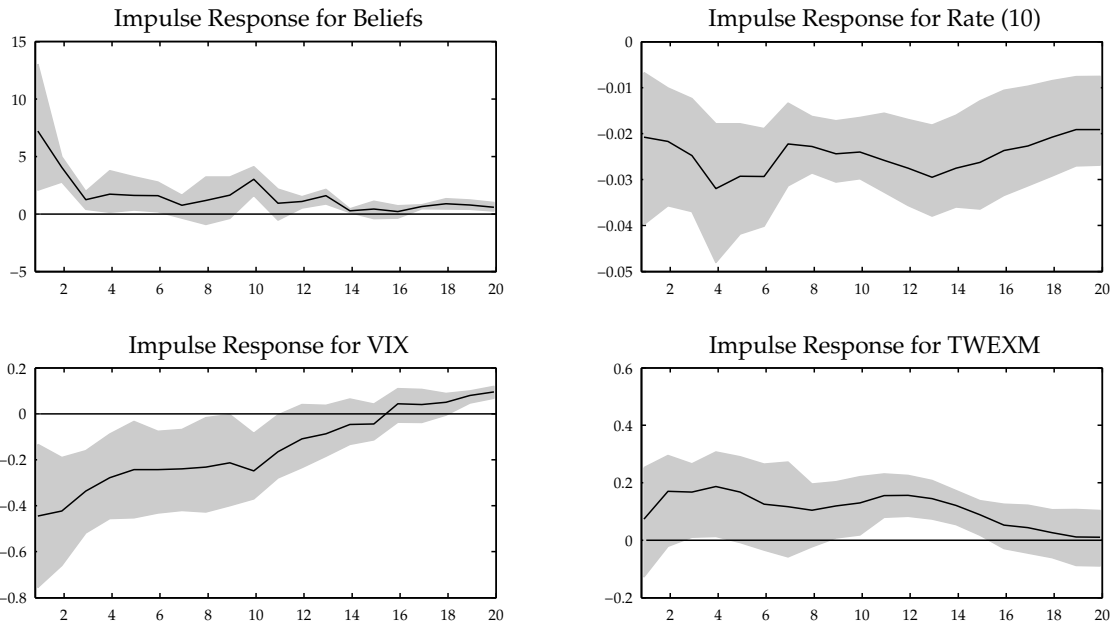


Figure 14: Impulse responses to shock to beliefs of late tapering: TWEXM

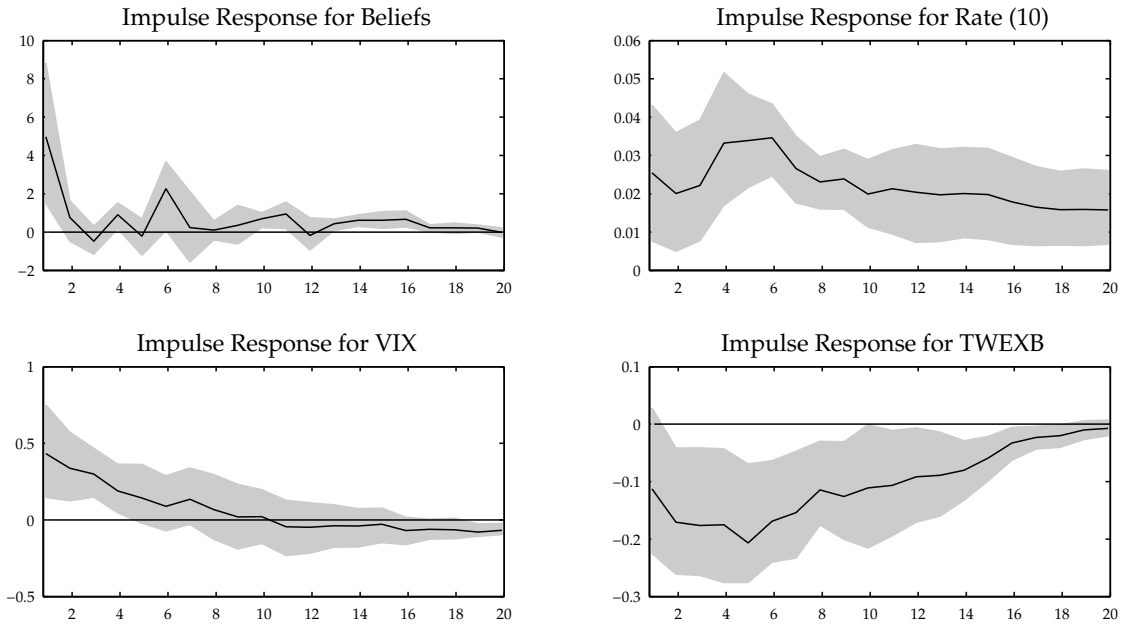


Figure 15: Impulse responses to shock to beliefs of early tapering: TWEXB

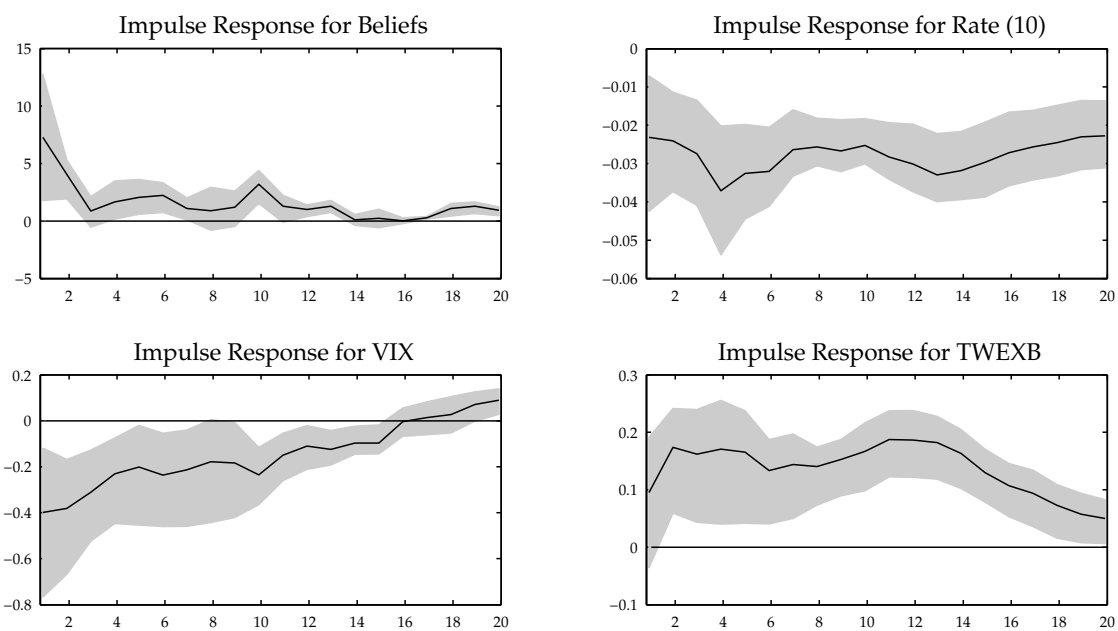


Figure 16: Impulse responses to shock to beliefs of late tapering: TWEXB

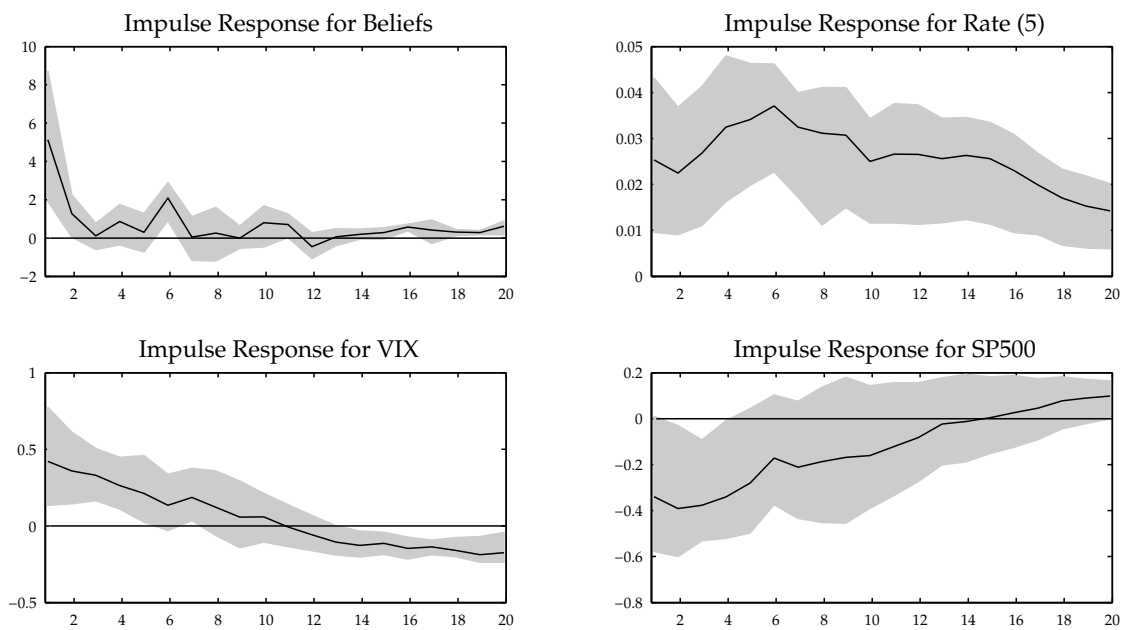


Figure 17: Impulse responses to shock to beliefs of early tapering: 5-year yield

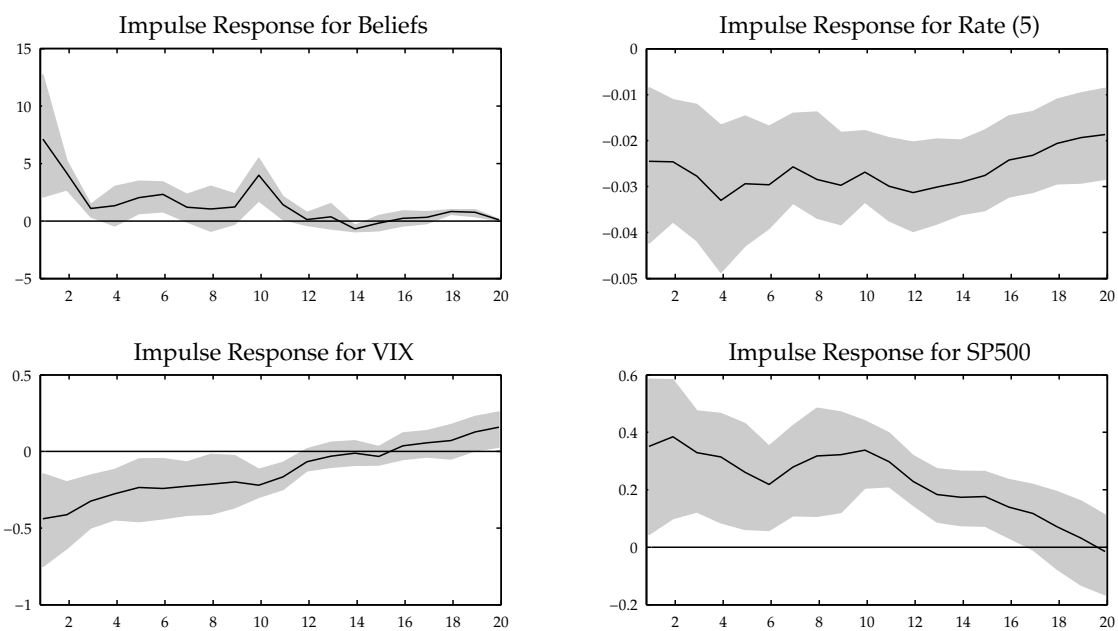


Figure 18: Impulse responses to shock to beliefs of late tapering: 5-year yield

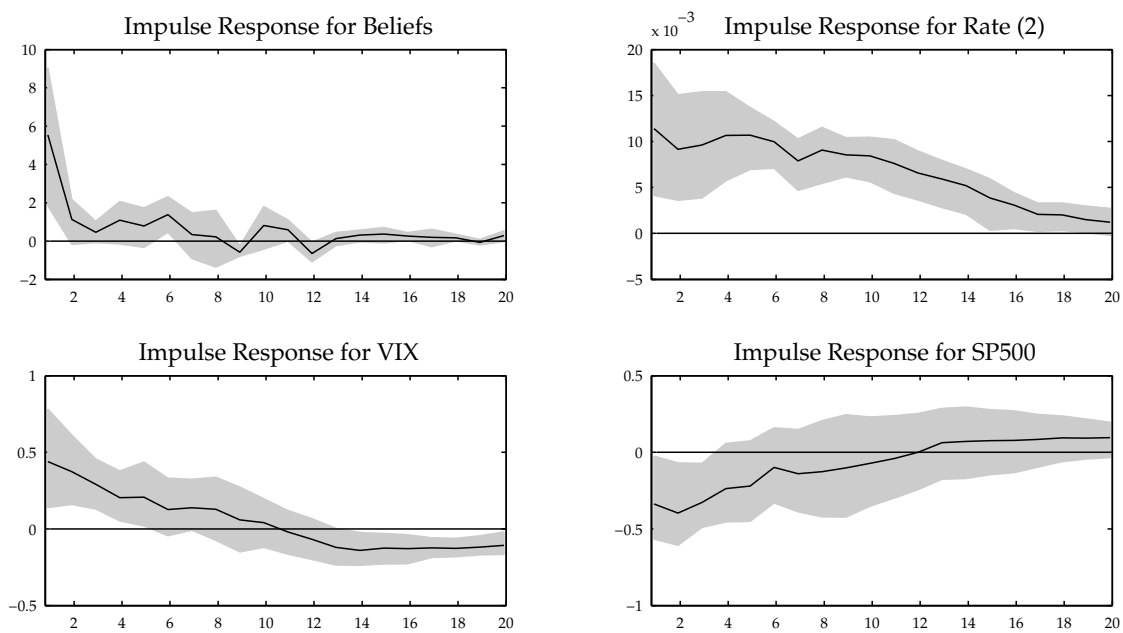


Figure 19: Impulse responses to shock to beliefs of early tapering: 2-year yield

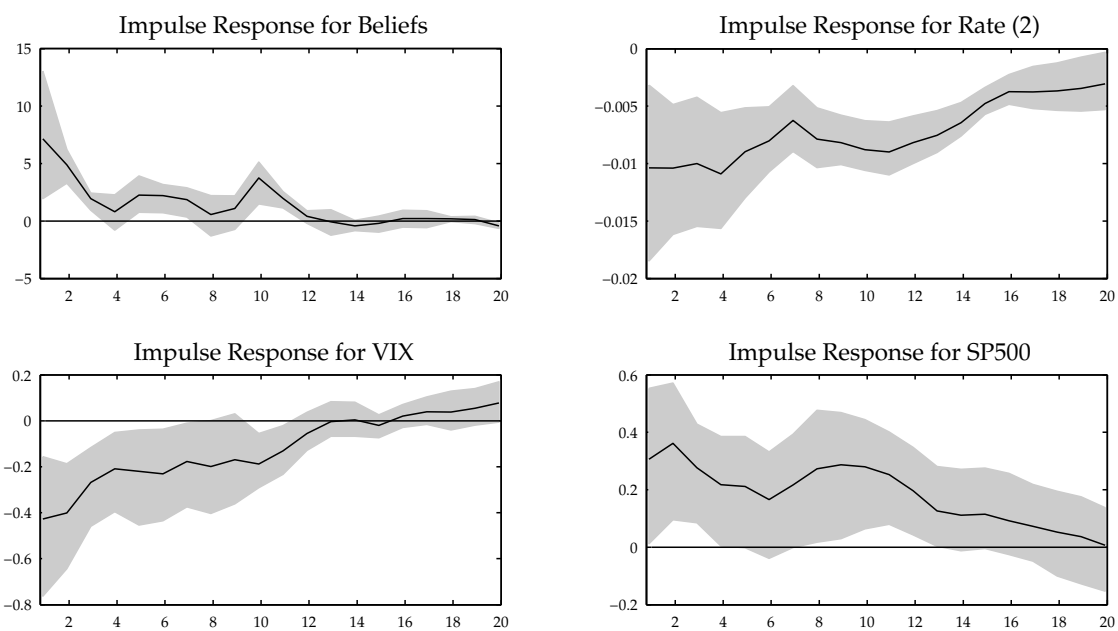


Figure 20: Impulse responses to shock to beliefs of late tapering: 2-year yield

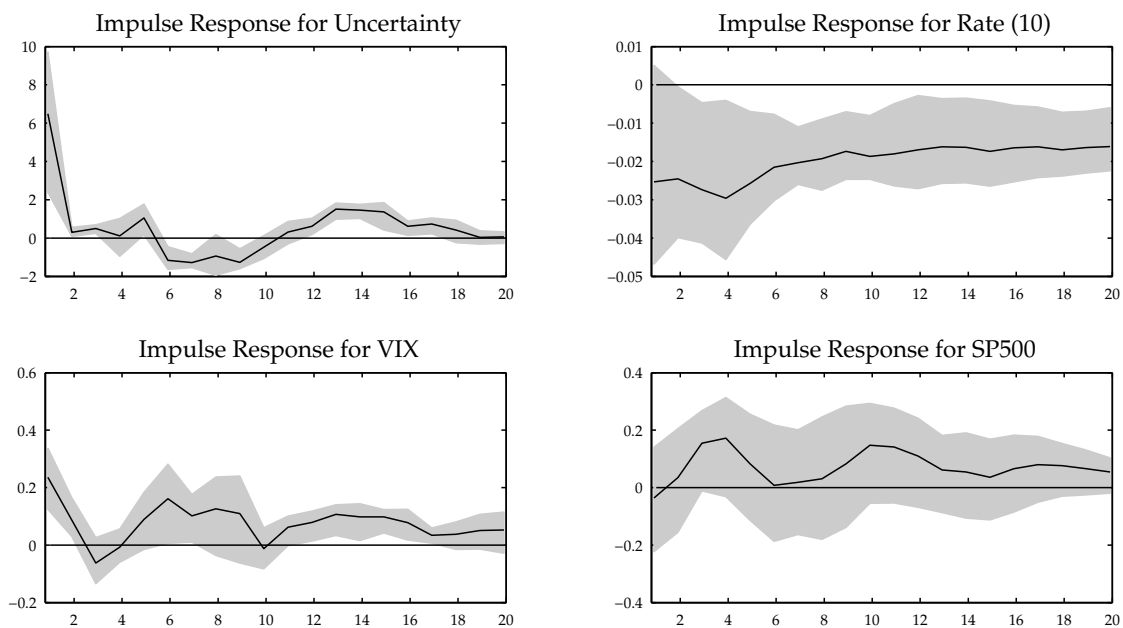


Figure 21: Impulse responses to shock to uncertainty: S&P500

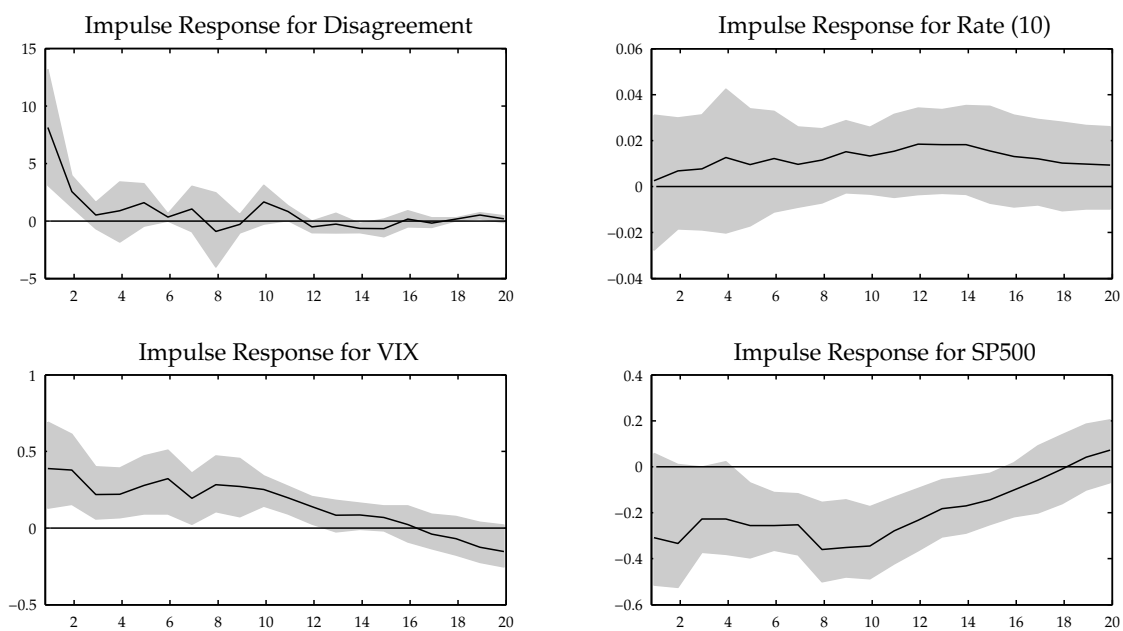


Figure 22: Impulse responses to shock to disagreement: S&P500

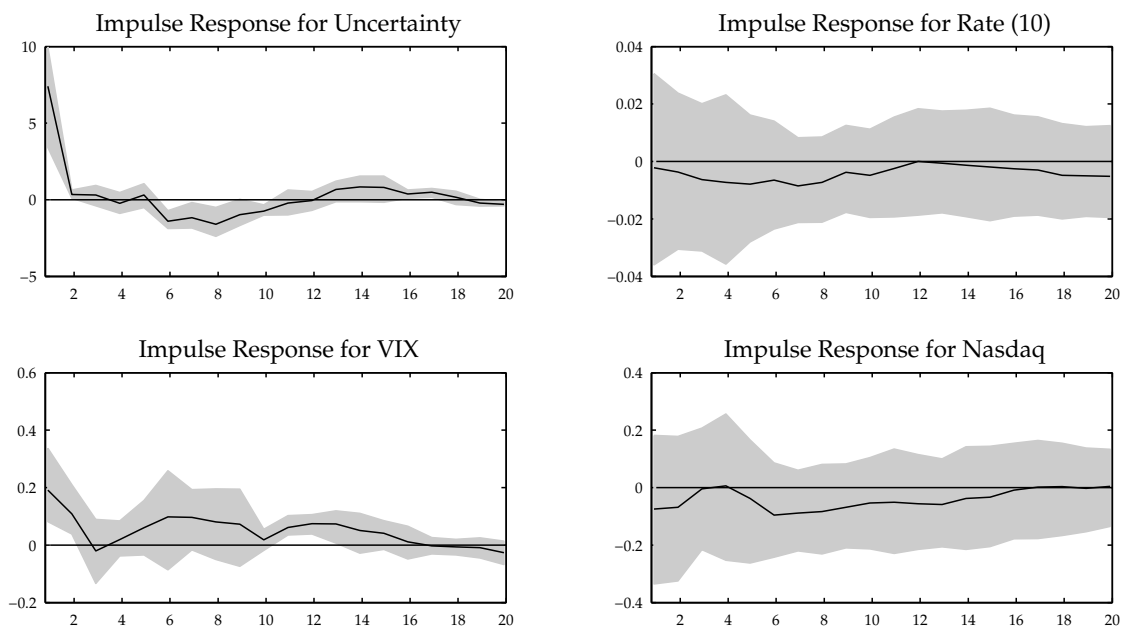


Figure 23: Impulse responses to shock to uncertainty: NASDAQ

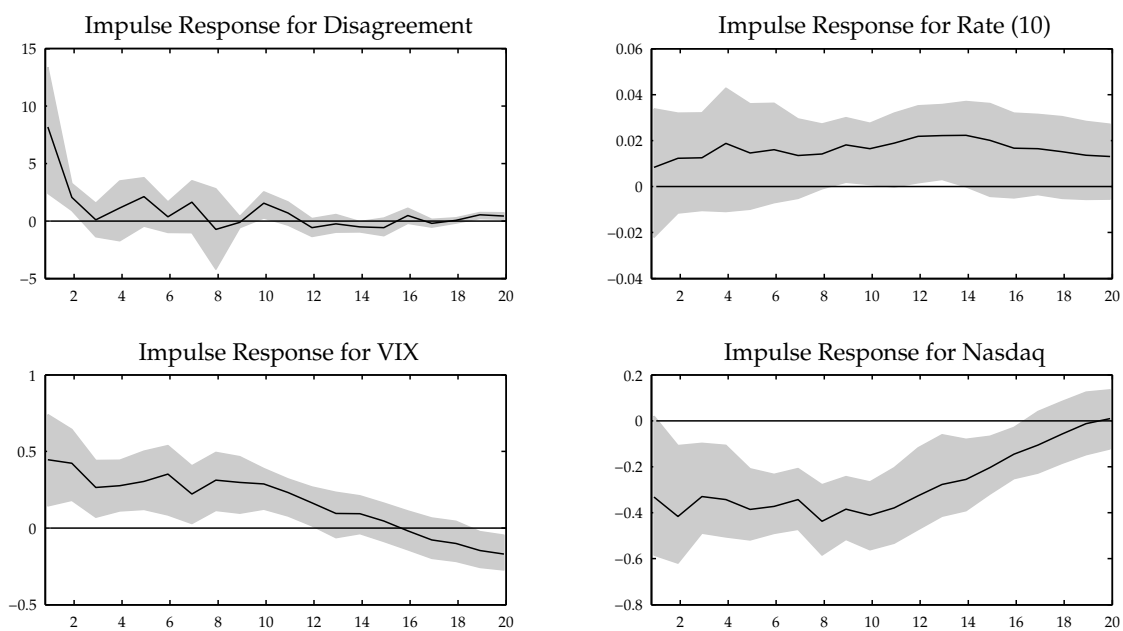


Figure 24: Impulse responses to shock to disagreement: NASDAQ

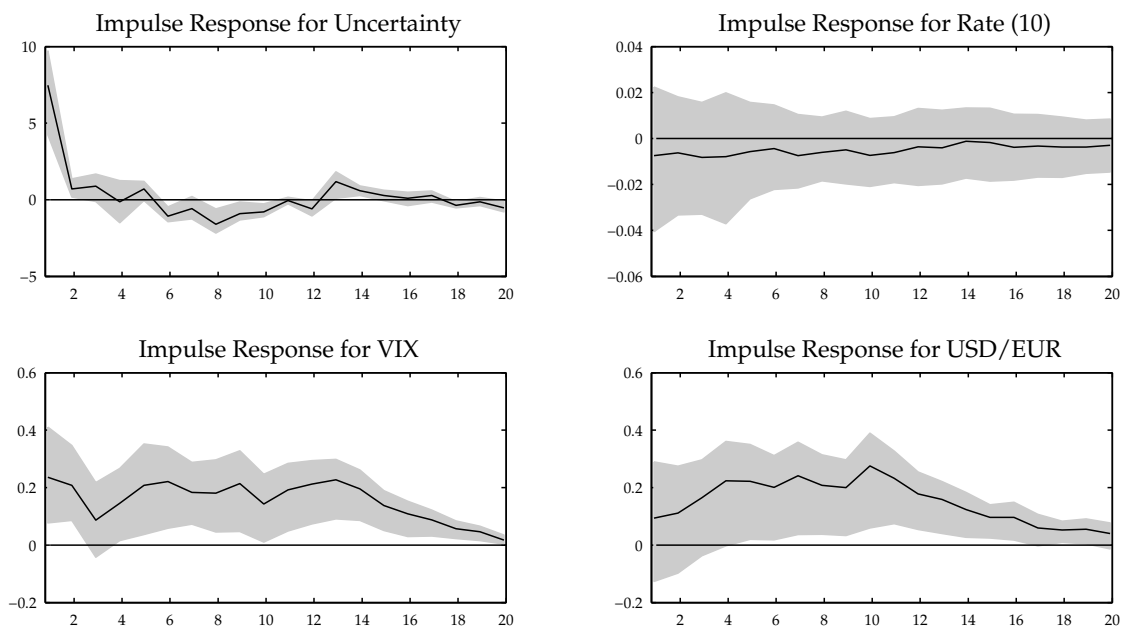


Figure 25: Impulse responses to shock to uncertainty: USD/EUR

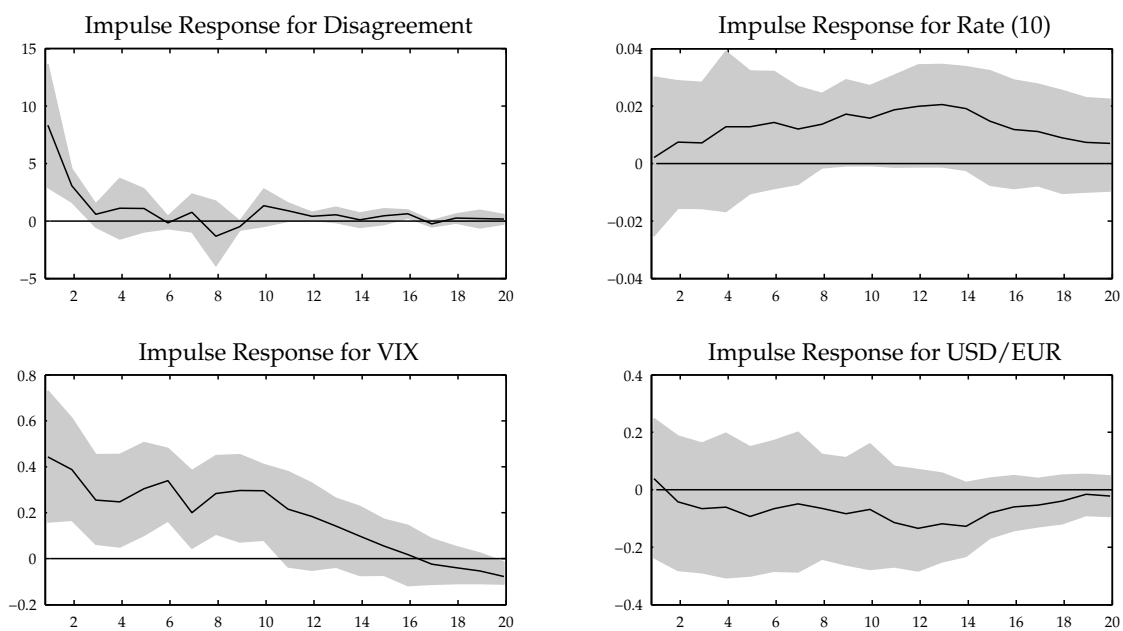


Figure 26: Impulse responses to shock to disagreement: USD/EUR

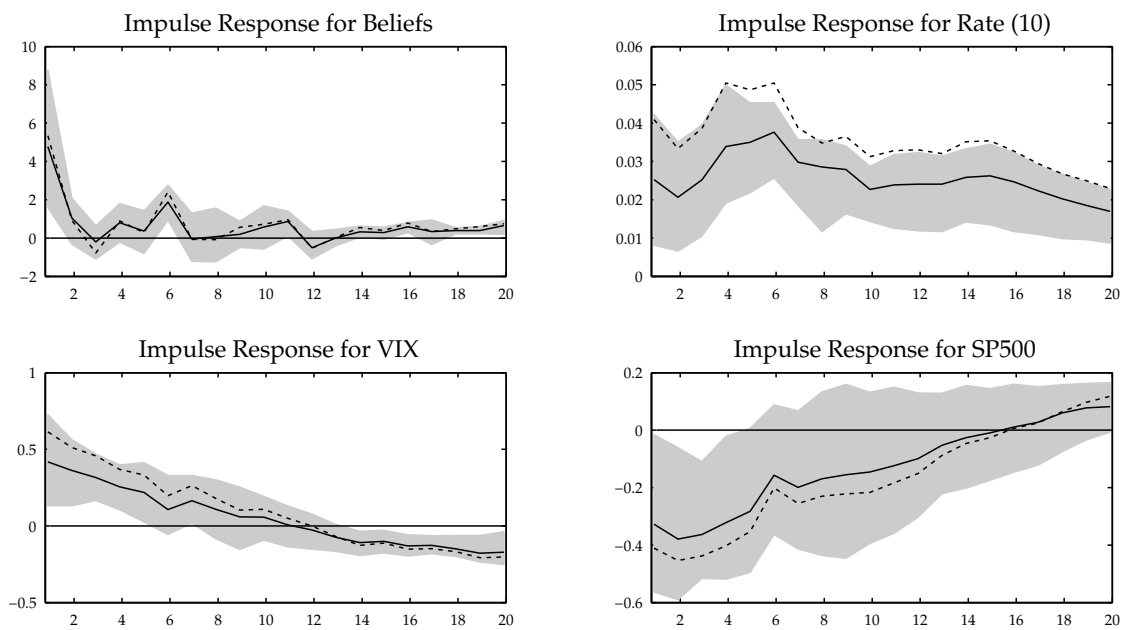


Figure 27: Impulse responses to shock in beliefs of early tapering: Fry/Pagan (2007)

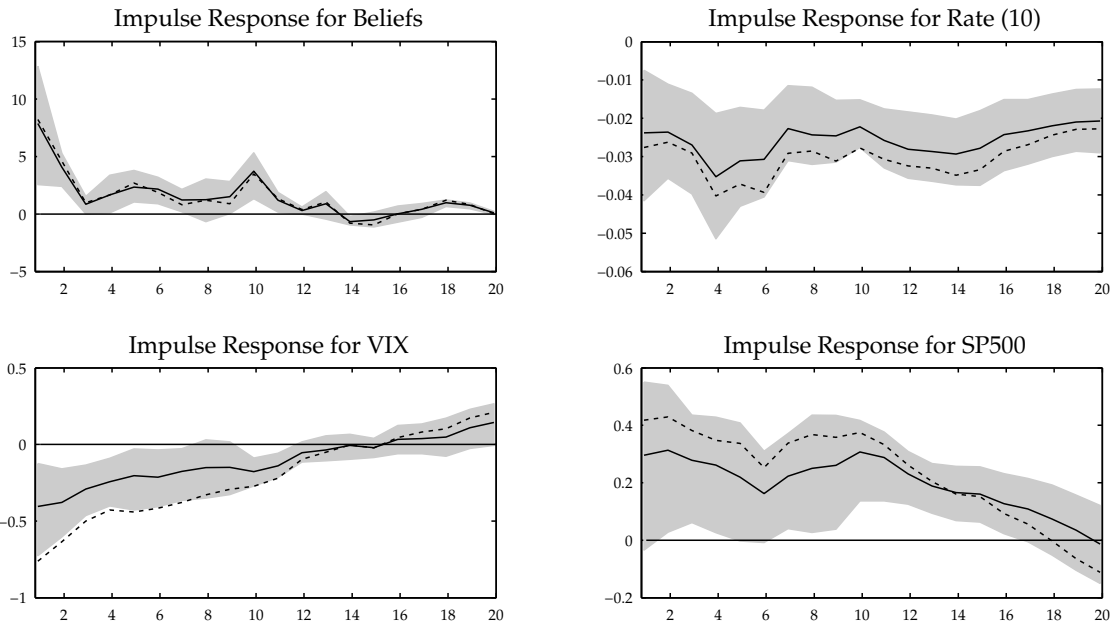


Figure 28: Impulse responses to shock in beliefs of late tapering: Fry/Pagan (2007)

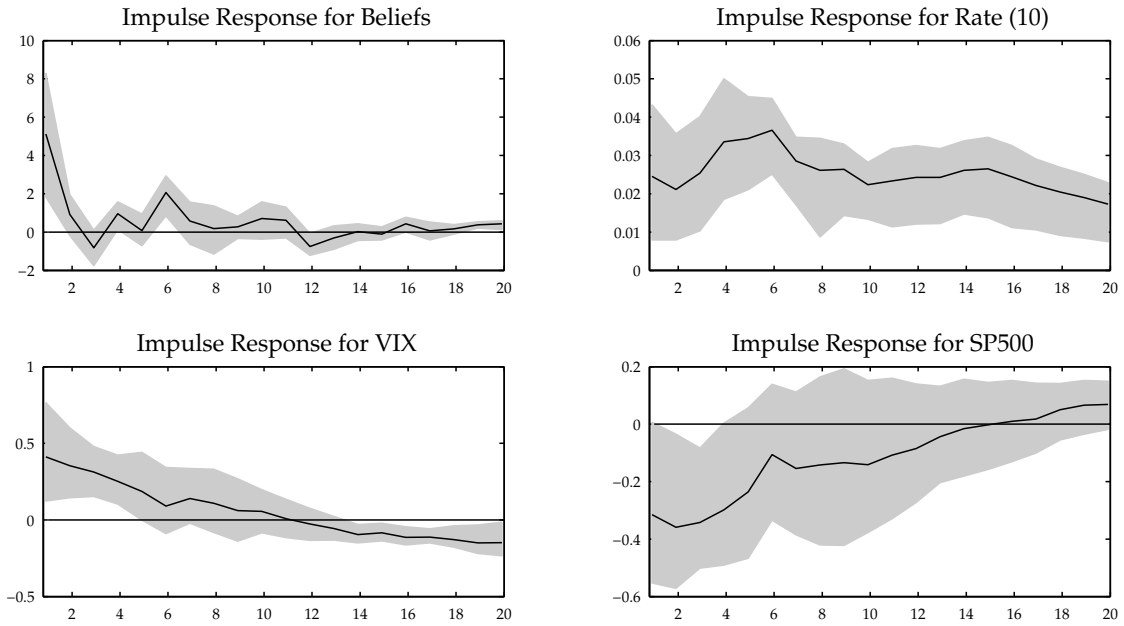


Figure 29: Impulse responses to shock in beliefs of early tapering: excluding retweets

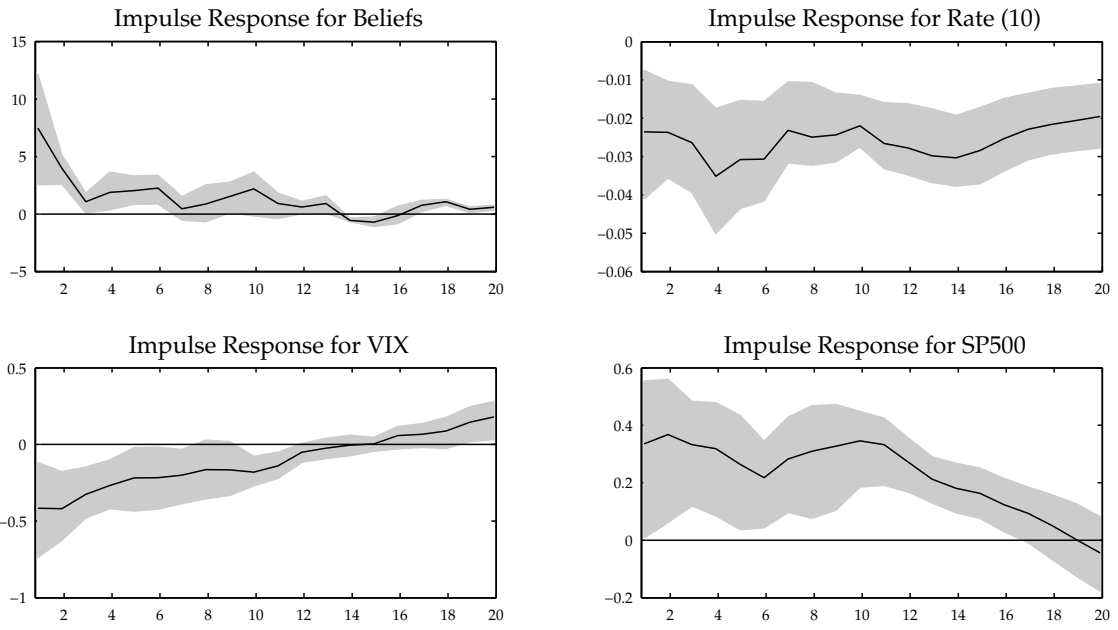


Figure 30: Impulse responses to shock in beliefs of late tapering: excluding retweets

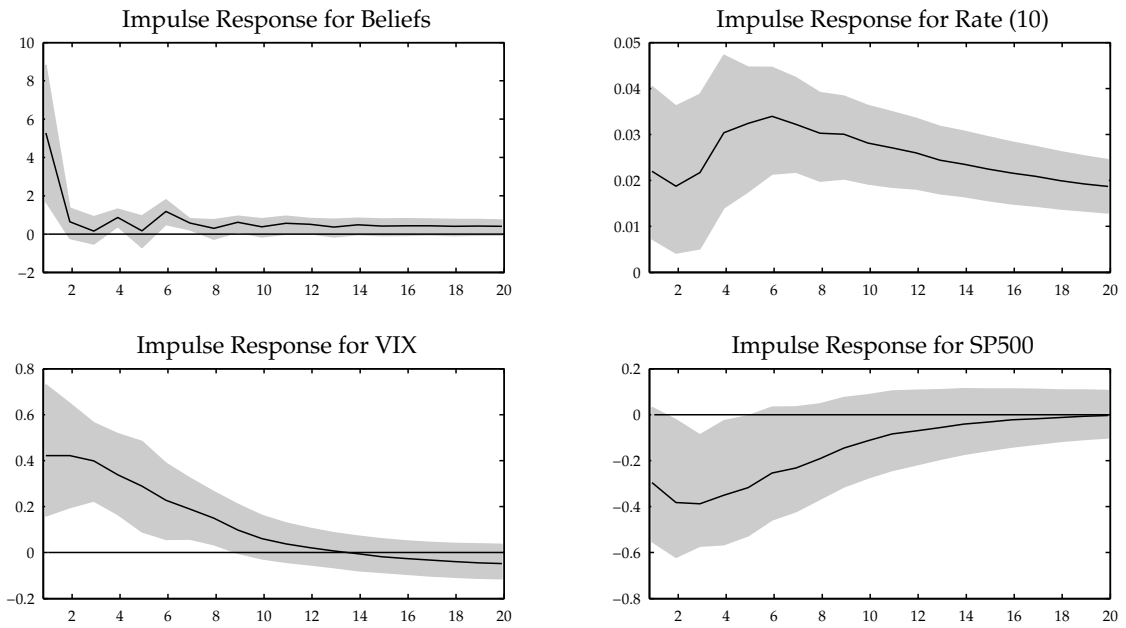


Figure 31: Impulse responses to shock in beliefs of early tapering: VAR(5)

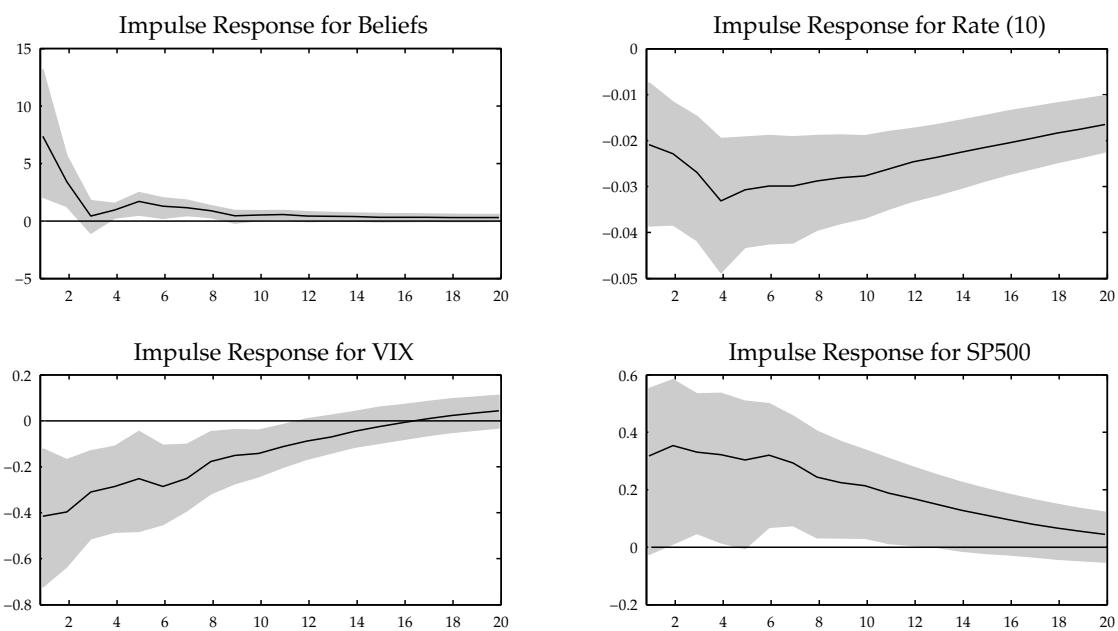


Figure 32: Impulse responses to shock in beliefs of late tapering: VAR(5)

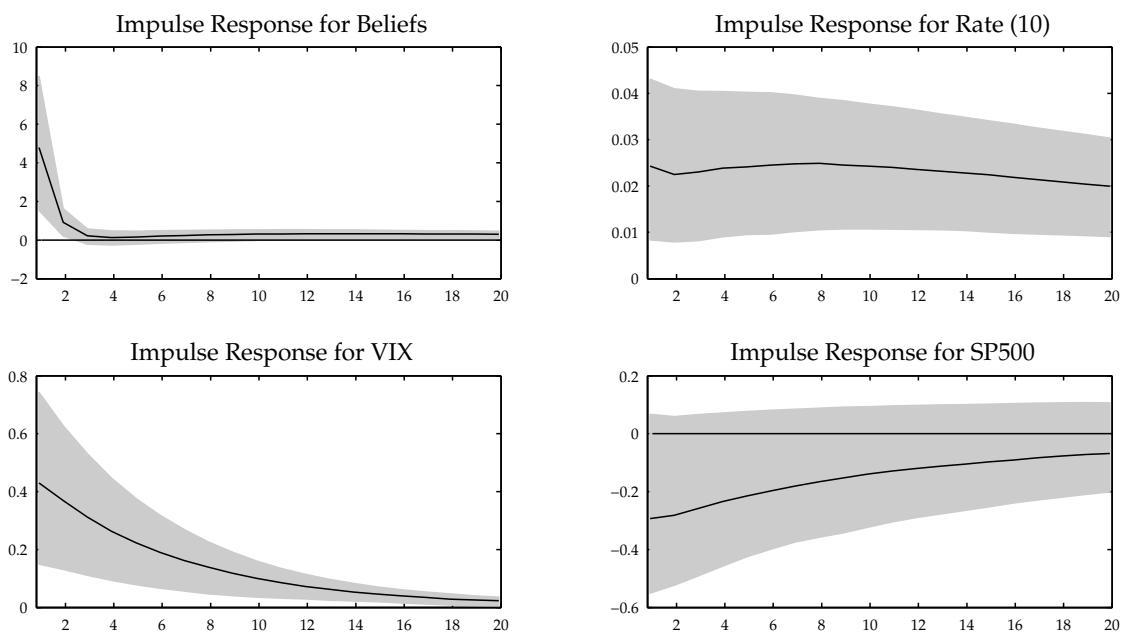


Figure 33: Impulse responses to shock in beliefs of early tapering: VAR(1)

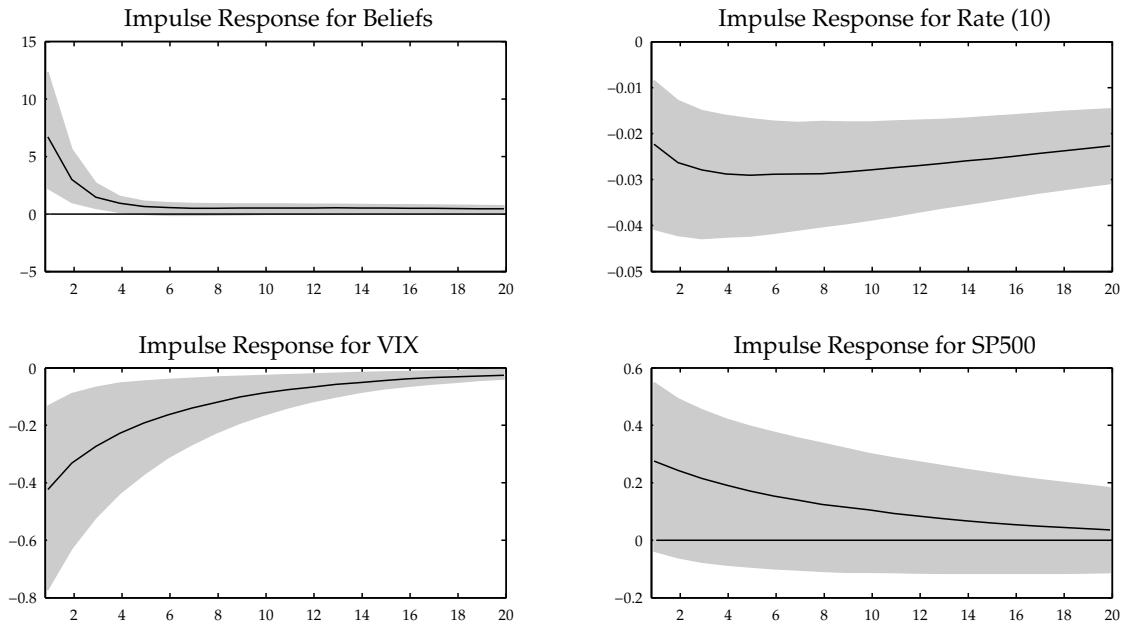


Figure 34: Impulse responses to shock in beliefs of late tapering: VAR(1)

Table 2: Forecast error variance decomposition

variable	impact of belief shock (in % of total variation)					
	<u>tapering soon</u>			<u>tapering late</u>		
	at horizon			at horizon		
	1 day	10 day	20 day	1 day	10 day	20 day
$Rate_t$	15.96	18.26	18.55	15.65	19.48	19.74
VIX_t	15.58	17.84	18.04	14.33	17.28	18.12
$Asset_t$	17.47	19.89	19.90	19.74	17.98	18.45

variable	impact of belief shock (in % of total variation)					
	<u>uncertainty</u>			<u>disagreement</u>		
	at horizon			at horizon		
	1 day	10 day	20 day	1 day	10 day	20 day
$Rate_t$	10.69	14.76	18.14	15.18	19.21	19.04
VIX_t	12.04	16.19	19.54	13.97	17.41	17.72
$AssetP_t$	12.36	16.39	18.93	18.08	20.62	20.53