Estimating the Fed's Unconventional Policy Shocks and Their Effects*

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Abstract

Fed's monetary policy announcements convey a mix of news about different kinds of conventional and unconventional policies and about the economy. Financial market responses to these announcements are very leptokurtic: often tiny, but sometimes large. I estimate the underlying structural shocks exploiting this feature of the data. I find standard monetary policy, Odyssean forward guidance, large scale asset purchases and Delphic forward guidance, and estimate their effects.

JEL classification: E52, E58, E44

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1 Introduction

Central banks deploy a growing arsenal of policies in their efforts to steer the economy, but measuring the effects of these policies is challenging. To address the endogeneity problem researchers increasingly follow Kuttner (2001) and use as instrumental variables the changes of financial asset prices in a narrow time window around Federal Open Market Committee (FOMC) announcements. Prior to the announcement, asset prices reflect the consensus view about the state of the economy and the Fed's expected response to it. After the announcement, asset prices incorporate also any unexpected news about the current and future fed funds rate policies, asset purchases and the Fed's view on the state of the economy. Consequently, the difference between the post- and pre-announcement asset prices, although purged of a large endogenous component of the Fed policy, still includes many different dimensions, which may affect the economy differently. Therefore, it is of crucial importance for monetary economics to separately identify their effects.

This paper studies the high-frequency reactions of financial markets to FOMC announcements and estimates the underlying structural, i.e. independent shocks. It finds that these shocks can be naturally labeled ex-post as the current fed funds policy, an "Odyssean" forward guidance (a commitment to a future course of policy rates), a large scale asset purchase and a "Delphic" forward guidance (a statement about the future course of policy rates understood as a forecast of the appropriate stance of the policy rather than a commitment, see Campbell et al. 2012). The paper then embeds these shocks in VAR models to estimate the different effects of these shocks on the economy.

To identify the structural shocks I exploit a striking, yet largely ignored feature of the data, namely that financial market reactions to FOMC announcement are very leptokurtic: often tiny, but sometimes large. I assume that the underlying shocks are independent. Independence in combination with excess kurtosis imply that a given observation is likely to be dominated by only a subset of the shocks. As a result, the shocks are identifiable from the data without the need for additional identifying assumptions. I specify a simple econometric model in which the responses of a vector of financial variables to FOMC announcements are driven by independent Student-t shocks, estimate it and back out the shocks.

More in detail, the baseline model expresses the surprises (i.e., the high-frequency reactions to FOMC announcements) in the near-term fed funds futures, 2- and 10-year Treasury yield and the S&P500 stock index as linear combinations of four Student-t distributed shocks. It turns out that these four shocks are very precisely estimated and ex post have natural economic interpretations. The first shock raises the fed funds futures, has less effect on the longer maturities and depresses the stock prices. It can be naturally labeled as the standard monetary policy shock. The remaining shocks do not affect the near-term fed funds futures. The second shock increases the 2-year Treasury yield the most and depresses the stock prices. It can be naturally labeled as the (Odyssean) forward guidance shock. The third shock increases the 10-year Treasury yield the most and plays a large role in some of the most important asset purchase announcements. It can be naturally labeled as the asset purchase shock. The fourth shock is similar to the Odyssean forward guidance shock, but triggers an increase, rather than a decrease, in the stock prices. Therefore, this shock matches the concept of Delphic forward guidance introduced by Campbell et al. (2012).

The findings of this paper are relevant for the ongoing research on the effectiveness of non-standard monetary policies. I track the effects of the estimated shocks using daily local projections and monthly VARs. I find persistent and significant effects of non-standard policies (forward guidance and asset purchases) on Treasury yields and, in the case of forward guidance, on corporate bond spreads. The effects on industrial production and consumer prices are less precisely estimated. I confirm the large and significant effects of standard monetary policy.

Also the Delphic forward guidance shocks have significant and persistent effects on the economy and occasionally contribute to the historical narrative of Fed policies. One of the largest Delphic shocks occurs in August 2011, when the Fed stated that near-zero interest rates will be warranted "at least through mid-2013", triggering pessimism about the economy.

Previous research has used a variety of approaches and assumptions to decompose the financial market reactions into economically interpretable components (see Gürkaynak et al., 2005; Inoue and Rossi, 2018; Cieślak and Schrimpf, 2019; Lewis, 2019; Swanson, 2020; Miranda-Agrippino and Ricco, 2020; Jarociński and Karadi, 2020, and others).

Most of these papers construct the shocks with the desired features and ignore their non-Gaussianity. For example, Gürkaynak et al. (2005) separate the target factor (standard monetary policy) and the path factor (forward guidance) imposing a zero restriction on the response of short term rates response to forward guidance. Swanson (2020) constructs the same two dimensions plus the large scale asset purchase shocks, minimizing the variance of the pre-Zero Lower Bound (ZLB) asset purchases shocks. Jarociński and Karadi (2020) separate monetary policy (a summary of standard and non-standard policies) from information shocks or Delphic forward guidance using sign restrictions. It is interesting that the first three shocks I estimate in the present paper are strikingly similar to the standard monetary policy (fed funds rate) shock, the forward guidance shock and the long-term interest rate/large scale asset purchase (LSAP) shock constructed by Gürkaynak et al. (2005) and Swanson (2020) even though I do not impose any of their assumptions. Furthermore, the fourth shock I estimate is highly correlated with the central bank information shock of Jarociński and Karadi (2020). Thus, my simple identification approach provides a validation of these papers' more involved assumptions.

Identification through non-Gaussianity, such as the excess kurtosis exploited here, has been known since the 1990s but economic applications have been few so far. This source of identification underlies the Independent Components Analysis (ICA) (Comon, 1994; Hyvärinen et al., 2001), which is widely used in signal processing, telecommunications and medical imaging. Bonhomme and Robin (2009) use ICA to identify factor loadings. Methodologically closest paper to the present one is Lanne et al. (2017) who identify structural VARs with Student-t shocks. Gouriéroux et al. (2017) extend the inference on Structural VARs to pseudo-maximum likelihood. Gouriéroux et al. (2020) show that also the Structural Vector Autoregression Moving Average (SVARMA) model is identified under shock non-Gaussianity. Recently, Braun (2021) applies identification through non-Gaussianity to the oil market.

There are analogies between identification by non-Gaussianity and identification by heteroskedasticity (Rigobon, 2003). Both approaches are examples of a statistical identification exploiting that shocks arrive "irregularly". For some recent applications of identification by heteroskedasticity see e.g. Lewis (2019, 2020); Brunnermeier et al. (2020). In particular, Lewis (2019) also identifies the effects of Fed's non-standard policies from high-frequency financial data, but his approach is very different from the present paper, as it relies on the intraday time variation of the volatility of asset prices on the days of FOMC announcements.

Economists commonly assume Gaussian shocks, where shock independence boils down to their orthogonality. Consequently, in the Gaussian case the researcher needs additional identifying assumptions to choose among the infinity of orthogonal rotations of the shocks. By contrast, in models with statistical identification, such as the non-Gaussian or heteroskedastic cases, the rotations are no longer equivalent and one can discriminate among them based on the data, for example using the likelihood function. This does not preclude imposing identifying restrictions or informative Bayesian priors. I do not do it in this paper but it would be a straightforward extension.

The fact that in the non-Gaussian or heteroskedastic case the likelihood function discriminates among the shock rotations sidesteps some controversial issues, such as the critique of the sign restrictions by Baumeister and Hamilton (2015), or the challenges of doing inference in set-identified models (e.g Giacomini and Kitagawa, 2020). However, since these statistical methods pin down the shocks only up to sign and permutation, in Monte Carlo methods one needs to address the technical challenges of shock normalization (Waggoner and Zha, 2003) and label switching, and this paper shows how to do it.

Section 2 presents the data, highlighting their excess kurtosis. Section 3 lays out the econometric model and explains the identification with a simple example. Section 4 reports the results from the baseline model and their sensitivity analysis. Section 5 tracks the longer term effects of the shocks using daily local projections. Section 6 embeds the shocks in a monthly VAR. Section 7 concludes.

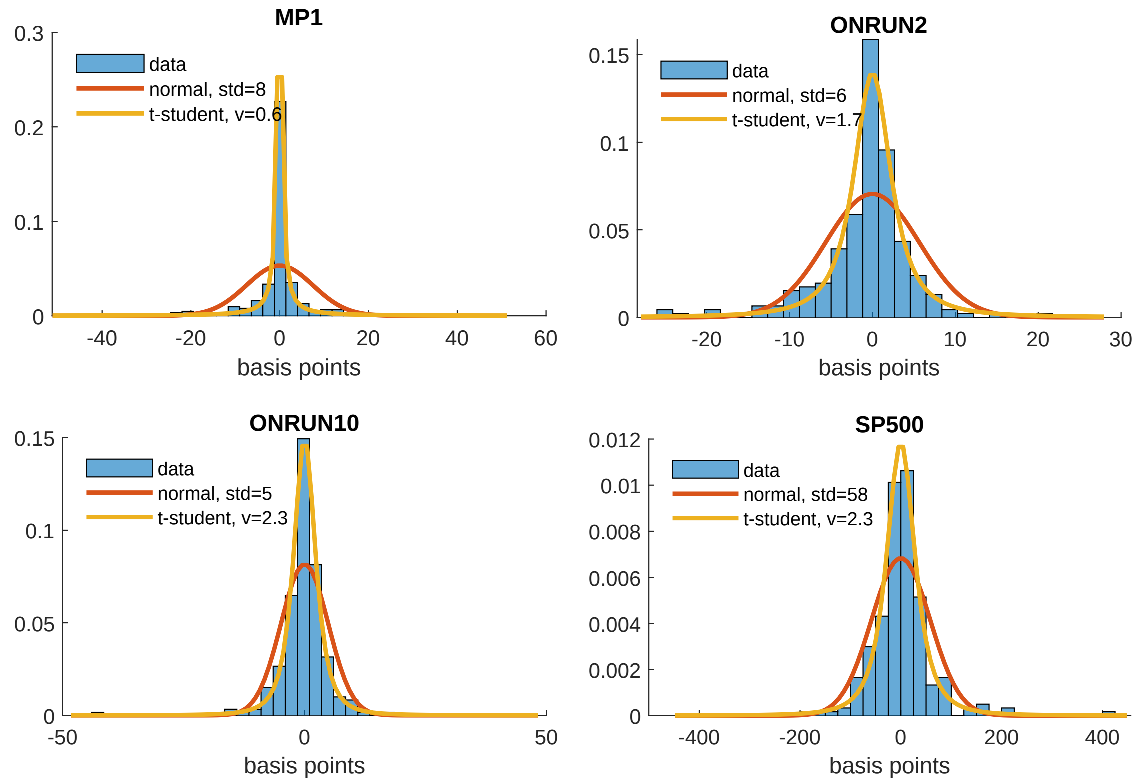
2 Data

The data on high-frequency financial market reactions to FOMC announcements come from the widely-used dataset of Gürkaynak et al. (2005) (GSS from now on). This dataset contains the changes of financial variables in a 30 minute window around FOMC announcements (from 10 minutes before to 20 minutes after the announcement). The sample studied here contains 240 FOMC announcements from July 1991 to May 2019.

In the baseline analysis I consider a vector of four variables. I refer to them using their well-known GSS database identifiers. MP1, or the first fed funds future adjusted for the number of the remaining days of the month (see GSS for details) is the expected fed funds rate after the meeting. ONRUN2 and ONRUN10 are the 2- and 10-year Treasury yields. Finally, SP500 is the Standard and Poors 500 blue chip stock index.

The choice of MP1, ONRUN2 and ONRUN10 follows Swanson (2020), who finds that these three variables approximately span the target, path and LSAP factors that he constructs.[1] I add the SP500 in order to capture the effects beyond the yield curve.

Figure 1: The empirical distributions of the baseline variables.



Note. Each plot contains the histogram of the data, the Gaussian density and the Student-t density each fitted into the data by maximum likelihood. The histograms are scaled so that they integrate to 1.

The responses of the four baseline variables to FOMC announcements are very non-Gaussian. Figure 1 reports, for each variable, the histogram, a Gaussian density and a Student-t density each fitted into the data by maximum likelihood. We can clearly see that

[1] Swanson (2020) reports that MP1, the part of ONRUN2 that is unexplained by MP1 and the part of ONRUN10 that is unexplained by MP1 and ONRUN2 have correlations respectively 96%, 96%, 89% with his target, path and LSAP factors.

the Gaussian densities, plotted in red, fit the histograms poorly. First, the Gaussian curves predict too few near-zero observations. Second, the observed 4-, 6- and even 8-standard deviation outliers are unlikely under the Gaussian distribution. The fitted Student-t densities, which agree with the histograms quite well, have very low shape parameters ($v = 0.6, 1.7, 2.3, 2.3$, respectively) implying very large departures from Gaussianity.

3 The econometric model

Throughout this paper I study the market responses to the FOMC announcements using the following simple econometric model:

$$y_t = C' \, u_t \qquad\qquad u_{n,t} \sim \text{i.i.d.} \mathcal{T}(0, 1, v). \tag{1}$$

$y_t = (y_{1,t}, ..., y_{N,t})'$ is the vector of N variables observed at time t. $u_t = (u_{1,t}, ..., u_{N,t})'$ is a vector of unobserved, structural, i.e. mutually independent, shocks. C is an $N \times N$ matrix whose i, j-th element $C(i, j)$ contains the effect of shock i on variable j. We are interested in independent shocks because only when they are independent it makes sense to discuss and interpret the effect of an individual shock.

$\mathcal{T}(0, 1, v)$ denotes the Student-t density with location parameter 0, scale parameter 1 and shape parameter v, with the probability density function satisfying

$$p(u_{n,t}) = c(v) \left(1 + u_{n,t}^2/v\right)^{-\frac{v+1}{2}}, \tag{2}$$

where $c(v) = v^{-1/2} B\left(\frac{1}{2}, \frac{v}{2}\right)^{-1}$ is the integrating constant, with $B(\cdot, \cdot)$ denoting the beta function.

Equation (1) is a special case of a Structural VAR with no lags of y_t. The case of no lags is relevant when variables y_t are approximately unpredictable, as is the case for the financial market responses to FOMC announcements studied in this paper.[2]

[2] Miranda-Agrippino and Ricco (2020) study the predictability financial market responses to FOMC announcements using their own lags and ten factors extracted from macroecnomics variables, and report unadjusted R-squared well below 0.1.

A sample of T observations satisfies

$$Y = U\,C, \tag{3}$$

where Y is the $T \times N$ matrix with y_t' in row t and U is the corresponding $T \times N$ matrix of structural shocks. It is convenient to reparameterize the model in terms of $W = C^{-1}$, so that we can write $YW = U$.

The log-likelihood of the sample Y is

$$\log p(Y|W, v) = T \log|\det W| - \frac{v+1}{2} \sum_t \sum_n \log(1 + u_{n,t}^2/v) + TN \log c(v), \tag{4}$$

where $u_{n,t} = y_t' w^n$, with w^n the n-th column of W. By maximizing the likelihood (4) we can estimate the set of shocks U and their effects $C = W^{-1}$.

The identification of this model depends crucially on the shocks being non-Gaussian. When the shocks are Gaussian the model is not identified and there are infinitely many versions of U and C that fit the data equally well. When the shocks are non-Gaussian, U and C can be estimated up to reordering and changing the signs. The pr

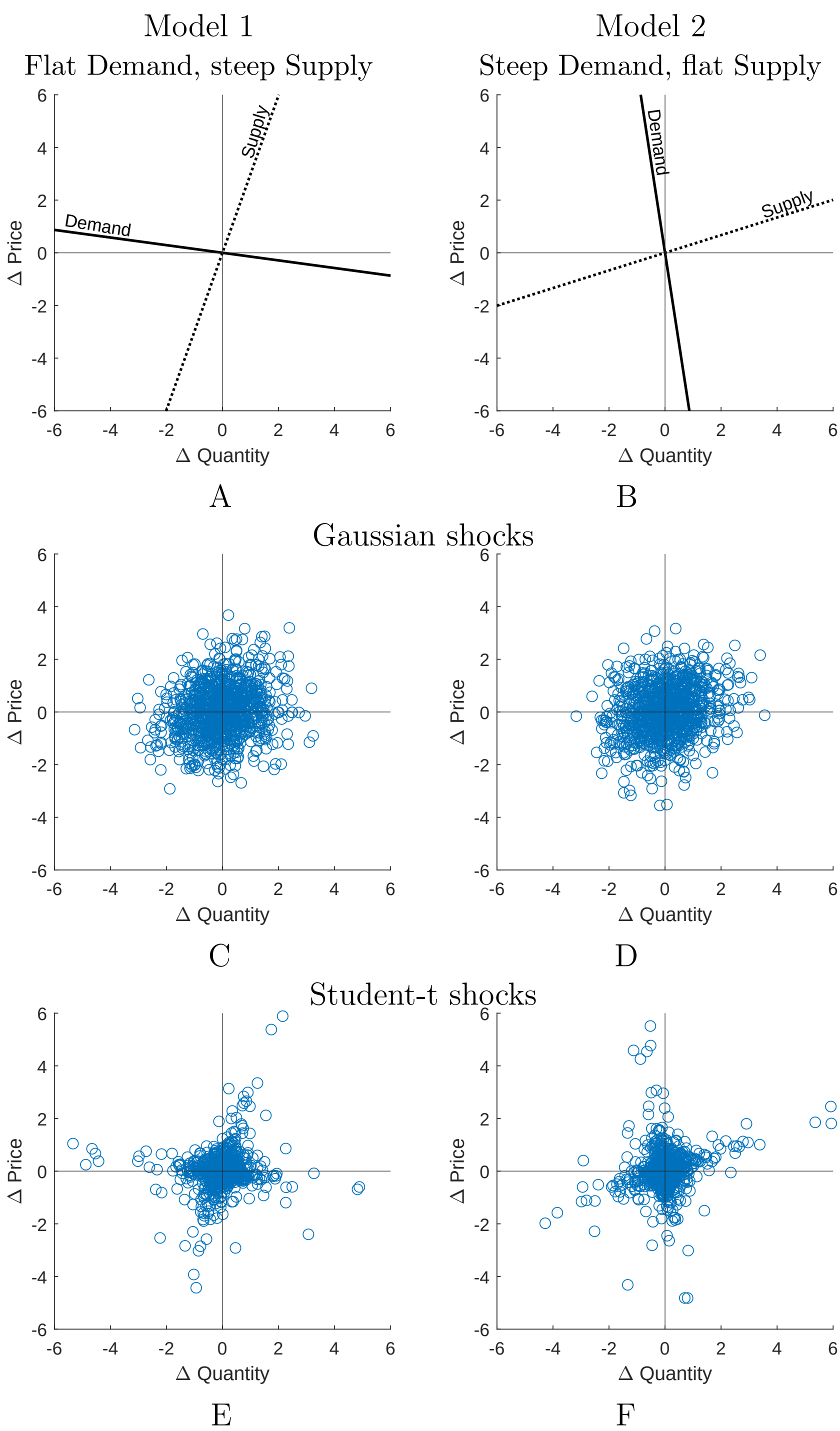
3.1 The intuition behind the identification

The purpose of this section is to provide a simple illustration how structural relationships get revealed in the data in the presence of excess kurtosis. For a formal proof that non-Gaussianity (of any form) of all but one shocks implies identification see e.g. Lanne et al. (2017), Proposition 2.

To fix ideas, consider the market for a good A. Market prices P and quantities Q are determined by demand and supply, each subject to shocks. Let us consider the innovations in P and Q in response to shocks, denoted ΔP and ΔQ. Can we identify the slopes of the demand and supply curves from the data on ΔP and ΔQ?

Consider two structural models. In Model 1 the demand schedule is relatively flat and the supply schedule is steep, while in Model 2 it is the reverse. Models 1 and 2 satisfy

Figure 2: Stylized example: demand and supply of good A.



Note. Each sample has 1000 observations. The samples in the left column are generated from (5) with coefficients C_1, and the samples in the right column are generated with coefficients C_2. In panels C and D the shocks d and s are independent Gaussian with mean 0 and variance 1. In panels E and F the shocks d and s are independent Student-t with mean 0, scale parameter 1 and shape parameter $v = 1.5$. Before feeding to the model, the Student-t shocks are re-scaled so that their sample variance equals 1. In all four scatter plots, ΔP and ΔQ have sample mean zero, sample variance 1 and sample correlation 0.2.

equation (5) with coefficients C_1 and C_2 respectively.

$$\begin{pmatrix} \Delta Q \\ \Delta P \end{pmatrix} = C'_{i\in\{1,2\}} \begin{pmatrix} s \\ d \end{pmatrix}, \text{ with } C'_1 = \begin{pmatrix} 0.94 & 0.33 \\ -0.14 & 0.99 \end{pmatrix}, \quad C'_2 = \begin{pmatrix} 0.14 & 0.99 \\ -0.94 & 0.33 \end{pmatrix}, \tag{5}$$

where s is a supply shock and d a demand shock. In Model 1 a unit supply shock s increases the quantity supplied by 0.94 while the market price falls by 0.14, revealing a flat demand curve with the slope of $-0.14/0.94 \approx -0.15$. The slope of the supply curve is $0.99/0.33 = 3$. In Model 2 the slopes are -6.7 and 0.33 respectively. Panels A and B of Figure 2 plot these demand and supply curves.

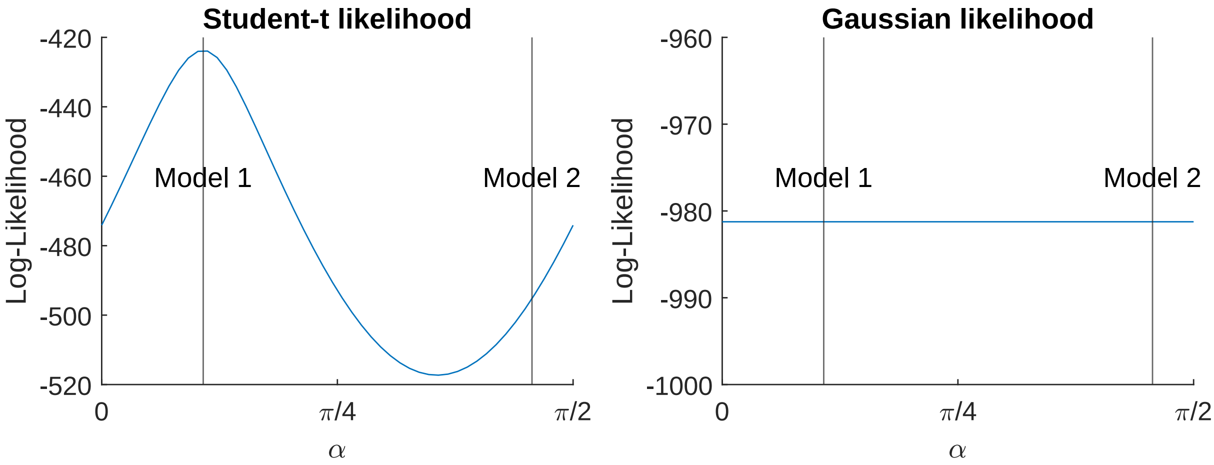
When the shocks s and d are Gaussian, we cannot identify the slopes from the data on ΔP and ΔQ. The second row of Figure 2 presents the combinations of ΔP and ΔQ obtained from Model 1 in panel C and from Model 2 in panel D, when the shocks d and s are drawn from independent Gaussian distributions with mean 0 and variance 1. In this example $C_1 \times C'_1 = C_2 \times C'_2 = \left(\begin{smallmatrix} 1 & 0.2 \\ 0.2 & 1 \end{smallmatrix}\right)$. Consequently, in both cases $(\Delta P, \Delta Q)$ are Gaussian with the same first two moments, (0, 0) and $\left(\begin{smallmatrix} 1 & 0.2 \\ 0.2 & 1 \end{smallmatrix}\right)$, so the samples look the same.

When the shocks s and d are independent Student-t, the situation changes. Now Models 1 and 2 produce systematically different ΔP and ΔQ. This is illustrated in the third row of Figure 2. The samples in the third row are generated from (5) but this time shocks d and s are drawn from a Student-t distribution with mean 0 and shape parameter $v = 1.5$. For consistency with the previous example, the shocks are re-scaled to ensure that their sample variance is 1. Hence, $(\Delta P, \Delta Q)$ continue to have the same first two moments, (0, 0) and $\left(\begin{smallmatrix} 1 & 0.2 \\ 0.2 & 1 \end{smallmatrix}\right)$. Nevertheless, the samples in panels E and F look very differently from each other and even an observer lacking any statistical training will have no problem matching each sample with the correct structural model.

What helps here is the high kurtosis of the Student-t distribution, i.e. the fact that the shocks are often tiny, but sometimes large. For an outlying observation, chances are that only one of the shocks was large, while the other was tiny. Hence, these observations cluster around the demand and supply schedules, revealing their slopes.[3]

[3]This example focuses on the identification resulting from a high kurtosis, because this is what the empirical application exploits. Other deviations from normality ensure identification as well. The online Appendix illustrates the identification coming from low kurtosis.

Figure 3: Stylized example: information in the likelihood function of the data from panel E of Figure 2.



Note. Likelihood of the sample in panel E of Figure 2, as a function of the rotation angle α. $\alpha = 0$ corresponds to the Choleski decomposition of the sample variance of Y. Left panel: Student-t likelihood given in (4). Right panel: Gaussian likelihood.

Obviously, if we can identify the structural model visually, we can also do it numerically by evaluating the likelihood function. Let Y be the $T \times 2$ matrix collecting the data on prices and quantities from panel E of Figure 2, i.e. generated from Model 1. Let U be the $T \times 2$ matrix with orthogonal shocks. We can decompose Y into orthogonal shocks in infinitely many ways because

$$Y = UC = UQ(\alpha)Q(\alpha)'C = \tilde{U}\tilde{C} \qquad \text{for any} \qquad Q(\alpha) = \begin{pmatrix} \sin\alpha & \cos\alpha \\ -\cos\alpha & \sin\alpha \end{pmatrix} \tag{6}$$

where $U'U = I = \tilde{U}'\tilde{U}$. Parameter α indexes all models that fit the data Y while implying different slopes of demand and supply. All these models have the same likelihood if we incorrectly assume that the shocks are Gaussian. However, the Student-t likelihood discriminates between these alternative models. This is illustrated in Figure 3.

The left panel of Figure 3 plots the log-likelihood of Y implied by the Student-t distribution of shocks, and given in (4). The log-likelihood peaks at the rotation angle α that corresponds to Model 1 in this example. At the α that corresponds to Model 2 the likelihood is 71 log points lower, so the likelihood ratio test would reject this model at any practical confidence level. Nevertheless, a researcher who wrongly assumes the Gaussian model would not be able to discriminate between the models. As the right panel of Figure 3 illustrates, the Gaussian likelihood is the same for any value of α. This is because the Gaussian likelihood depends only on the first two moments and all values of α produce models with the same first two moments. However, incorrect values of α imply shocks that exhibit particular relations between demand and supply shocks, such as their co-kurtosis, in order to match the data in panel E. This violates the independence of the shocks and hence gets penalized in the Student-t likelihood.

The rest of the paper investigates whether the non-Gaussianity of the FOMC policy surprises reveals the slopes of structural relations similarly as in the above example. In this real-life case no bi-variate scatter-plot of the variables from the GSS dataset looks like panels E and F of Figure 2, so clearly one needs to consider more than two variables and two shocks. The hope is that in the data is informative enough to pin down a sufficient number of distinct shocks and that the independence assumption is reasonable enough to yield interpretable shocks.

3.2 Estimation

I estimate model (1) and conduct inference on the structural shocks and their impacts on the variables. I use the maximum likelihood estimation to obtain $\hat{W}$ and $\hat{v}$, the estimate of the structural shocks $\hat{U} = Y\hat{W}$, the estimate of the impact matrix $\hat{C} = \hat{W}^{-1}$ and other quantities discussed later. To assess the estimation uncertainty I simulate the exact shape of the likelihood using the Metropolis-Hastings algorithm.

3.2.1 Maximum likelihood

I maximize the likelihood function (4). The Appendix provides the analytical expression for the gradient. One peculiarity of model (1) is that it is only identified up to a permutation of the shocks and up to scaling each shock by +/-1. The likelihood $p(Y|W)$ is invariant to permuting the columns of W ($N!$ possibilities) and flipping their signs (2^N possibilities), and consequently it has $N! \times 2^N$ equally high modes. The maximization routine converges to one of these modes, $\hat{W}$, which corresponds to a particular ordering and signs of the shocks. I compute the asymptotic variance of $(\operatorname{vec}\hat{W}', \hat{v})'$ as $\mathcal{V} = (-\mathcal{H})^{-1}$, where $\mathcal{H}$ is the Hessian of the log-likelihood at $\hat{W}, \hat{v}$.

3.2.2 Simulation of the shape of the likelihood with the Metropolis-Hastings algorithm

Next I use the Metropolis-Hastings algorithm to draw a sample of parameter values from the distribution proportional to the likelihood. This has two purposes. First, I want to explore the shape of the likelihood function in order to detect potential identification problems. Second, I want the inference about nonlinear functions of W, such as the C, to be as precise as possible. With a sample from the Metropolis-Hastings algorithm I can assess the uncertainty about all quantities of interest precisely without relying on asymptotic approximations.

Simulation. I start the simulation from the maximum likelihood estimate $\hat{W}, \hat{v}$. I generate proposal draws with a random walk model with the innovation variance equal to the asymptotic variance $\mathcal{V}$ scaled to ensure the acceptance rate of about 20%. The scale is 0.66 in the baseline model. I generate 10,000,000 draws and keep every 10,000-th. This simulation takes less than 5 minutes on a standard laptop.

Normalization. The Metropolis-Hastings chain may visit the neighborhoods of different modes. As a consequence, given a draw of W one does not know to what ordering and signs of the shocks it corresponds. The draw needs to be normalized, i.e. mapped into the same ordering and signs of the shocks as in $\hat{W}$. I proceed in two steps. First, I fix the signs of the shocks for each permutation. Second, I pick one of the (up to) $N!$ permutations, choosing the one that has *the highest probability under the Gaussian approximation of the likelihood function around* $\hat{W}$.

Let $\tilde{W}$ denote a draw of W, let $p = 1, ..., N!$ index the permutations of the N columns of $\tilde{W}$, let $\tilde{W}_p$ denote the matrix obtained by the p-th permutation of the columns of $\tilde{W}$, let $\mathcal{V}_W$ denote the asymptotic variance of $\operatorname{vec} W$ (i.e., $\mathcal{V}$ without the last row and column) and let $F(x|m, V)$ denote the multivariate Gaussian density with mean m and variance V evaluated at the point x.

Algorithm 1 *Given a draw* $\tilde{W}$*, for each permutation* $\tilde{W}_p$*,* $p = 1, ..., N!$*:*

1. *Scale the columns of* $\tilde{W}_p$ *by +/-1 using the Likelihood Preserving normalization of*

Waggoner and Zha (2003) (their Algorithm 1), obtaining a sign-normalized matrix $\tilde{W}_p^{LP}$.

2. *Evaluate* $f(p) = F(\mathrm{vec}\, \tilde{W}_p^{LP} | \, \mathrm{vec}\, \hat{W}, \mathcal{V}_W)$.

Take the $\tilde{W}_{p*}^{LP}$ *where* $p* = \arg\max_p f(p)$ *as the normalized* $\tilde{W}$.

In practice a finite Markov Chain does not visit the neighborhoods of all the modes but only a subset of them, so I only need to consider the permutations of those columns of W that have multiple modes before the normalization, rather than all the $N!$ permutations. This speeds up the normalization.

The baseline model (defined below) estimated on the full sample is an extreme case, because the different modes of its likelihood are well separated by regions of a low likelihood. As a result, a 10,000,000 long chain with the standard, 20% acceptance rate is unlikely to visit the neighborhood of another mode. However, for larger models and for models estimated on subsamples the chains do visit neighborhoods of multiple modes and the normalization sometimes becomes more time consuming than the simulation itself.

4 Estimation results

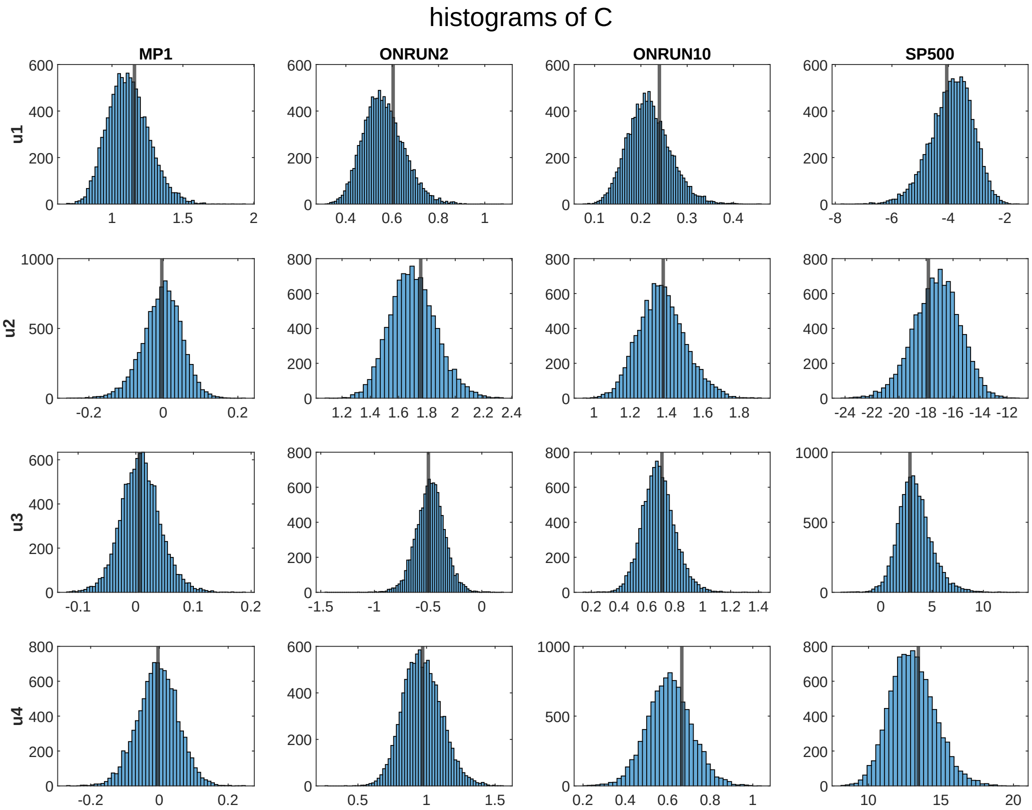
4.1 The baseline model

I define y_t=(MP1, ONRUN2, ONRUN10, SP500), estimate model (1) by maximum likelihood and then simulate the shape of the likelihood.

Figure 4 reports the distribution of the elements of C obtained with the simulation. Vertical lines represent the maximum likelihood estimates and the histograms represent the distribution of the draws from the Metropolis-Hastings algorithm. The distributions look approximately Gaussian and, ex post, yield very similar inferences as the asymptotic distribution of the maximum likelihood estimates. However, next subsections report some models where the likelihood functions have less regular shapes and the simulation-based inference matters.

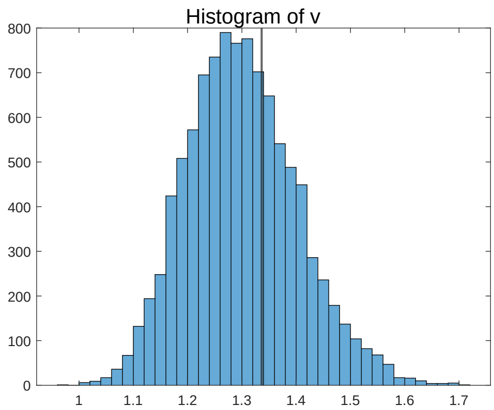
Figure 5 reports the distribution of the degree of freedom parameter v. The maximum likelihood estimate is 1.33 and virtually all the probability mass lies between 1 and 2, implying a very leptokurtic distribution.

Figure 4: The distribution of C



Note: Histograms of the elements of C based on the Metropolis-Hastings chain. Black vertical lines represent the maximum likelihood estimates.

Figure 5: The distribution of v

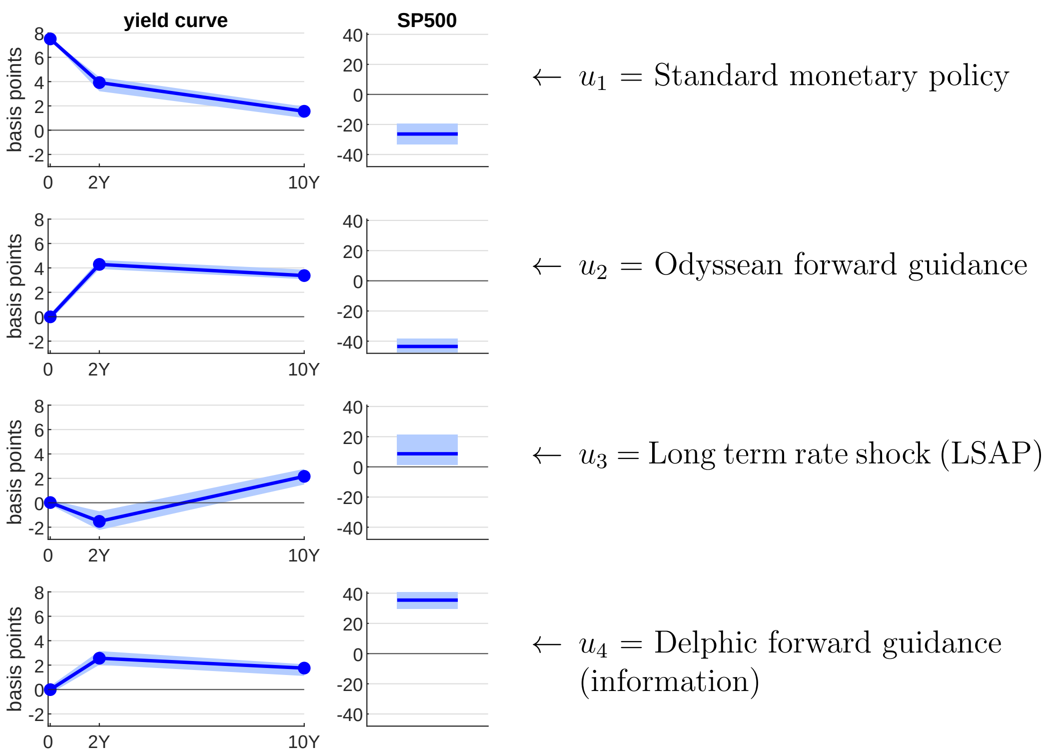


Note: Histogram of v based on the Metropolis-Hastings chain. The black vertical line represents the maximum likelihood estimate.

4.2 The impact effects of the four baseline shocks

Figure 6 reports C in a more convenient way. First, C gives the responses of Y to a unit shock, but it is easier to interpret and compare with the previous literature the effects of a one standard deviation shock. Although the standard deviation of u is not defined for the Student-t density with $v \leq 2$, but one can always compute the standard deviation of $\hat{U} = Y\hat{W}$. Therefore, in the following plots I re-scale the entries in each row of C by the sample standard deviation of the corresponding shock (the corresponding column of $\hat{U}$). Second, for a more convenient interpretation of the coefficients I now switch to reporting only their modes and the 95% probability ranges (the ranges between quantiles 0.025 and 0.975). Third, I plot the responses of interest rates against the x-axis showing their maturity. Figure 6 shows this more convenient presentation of C and Table 1 provides the underlying numbers for reference.

Figure 6: The responses of the variables to standardized shocks, 95% band.



The shocks reported in Figure 6 are tightly estimated and have intuitive economic interpretations.

u_1 looks like a standard contractionary monetary policy shock. The fed funds rate

Table 1: The responses of the variables to standardized shocks

	MP1	ONRUN2	ONRUN10	SP500
u_1	7.51	3.92	1.56	-26.35
	(0.03)	(0.30)	(0.23)	(3.50)
u_2	-0.01	4.29	3.37	-43.50
	(0.13)	(0.19)	(0.19)	(2.31)
u_3	0.02	-1.52	2.17	8.66
	(0.11)	(0.38)	(0.32)	(4.84)
u_4	-0.01	2.56	1.76	35.43
	(0.16)	(0.29)	(0.24)	(2.77)

Notes. Standard deviations in parentheses. The same coefficients are reported graphically in Figure 6.

increases by 7.5 basis points and other interest rates follow, with a weaker effect for longer maturities. The 2-year Treasury yield increases by almost 4 basis points and the 10-year Treasury yield by about 1.6 basis points. The SP500 index drops by 26 basis points.

u_2 looks like the effect of forward guidance. The fed funds rate does not change in the near term, but the 2-year yield increases by more than 4 basis points and the 10-year yield by 3.4 basis points in the half-hour window around the FOMC announcement. This shock is very contractionary and the SP500 drops by 44 basis points.

u_3 is essentially an idiosyncratic shock to the 10-year yield, because it has little effect on anything else: only the 2-year rate falls a little. However, I show below that this shock has a significant impact on the stock market in the later part of the sample and its realizations coincide reasonably with large asset purchases, which justifies calling it an LSAP shock.[4]

Finally, u_4 moves the yield curve similarly as the forward guidance shock u_2, only is about two-thirds of the size. However, by contrast to u_2, this shock is accompanied by an *increase* in the SP500 index by 35 basis points, suggesting the activation of the information effect. In particular, this shock perfectly matches the notion of the Delphic forward guidance of Campbell et al. (2012).

[4] Swanson (2020) also finds that his LSAP shock has an insignificant effect on the stock prices in the full sample.

Table 2: Variance decomposition

	MP1	ONRUN2	ONRUN10	SP500
u_1	**1.00**	**0.36**	**0.11**	**0.18**
	(0.00)	(0.04)	(0.03)	(0.04)
u_2	0.00	**0.43**	**0.53**	**0.48**
	(0.00)	(0.04)	(0.07)	(0.03)
u_3	0.00	0.05	**0.22**	0.02
	(0.00)	(0.03)	(0.06)	(0.03)
u_4	0.00	**0.15**	**0.14**	**0.32**
	(0.00)	(0.03)	(0.03)	(0.06)
Total	1.00	1.00	1.00	1.00

Note: Shares of the sample variance. Standard deviations in parentheses.

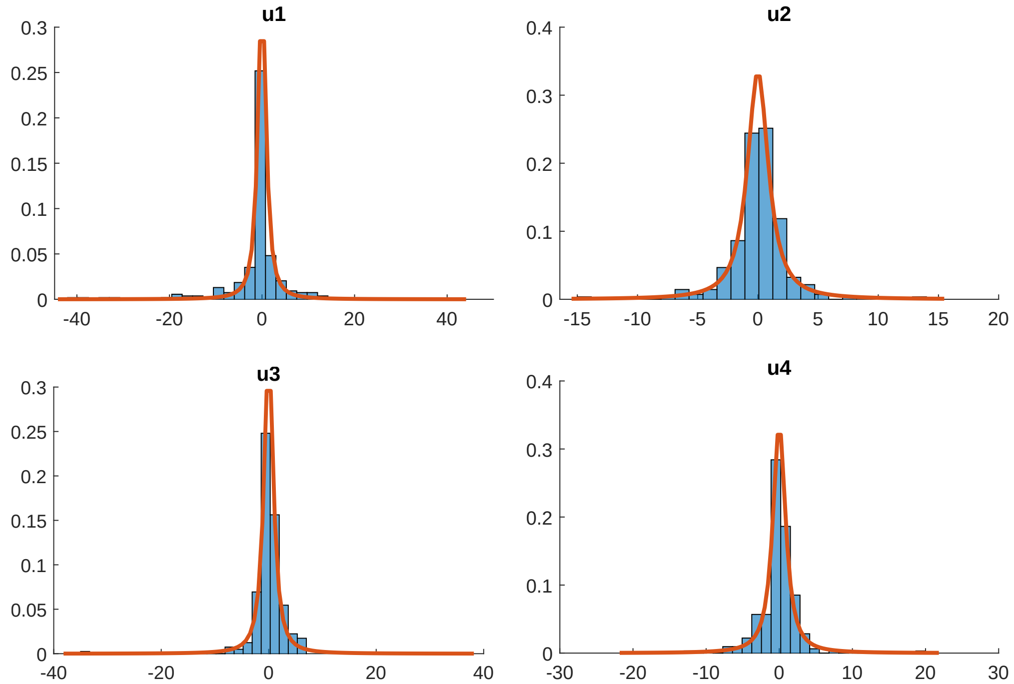
Since the shocks do not have a well-defined variance, also variance decompositions need to be taken with a grain of salt and we should expect them to be sensitive to outliers. Table 2 reports the variance decompositions of all variables, which should be interpreted with this caveat. u_1 is simply equal to MP1. In light of this, the federal funds rate surprises are a valid instrument for the standard monetary policy shock (e.g. Kuttner (2001); Bernanke and Kuttner (2005) use this instrument). However, the most important shock is the Odyssean forward guidance shock u_2, which accounts for 43% of the variation of 2-year bond yields and about a half of the variation of 10-year bond yields and stock prices in the half-hour windows around FOMC announcements. The third shock that is pervasive, in the sense that it accounts for non-trivial shares of multiple variables, is the Delphic forward guidance shock u_4. It accounts for about 15% of the variation of Treasury yields and one third of the variation of stock prices.

The effects of u_1 and u_2 on MP1 and Treasury yields reported in Table 1 are very similar to the effects of the target factor and path factor of GSS and Swanson (2020) (compare with Swanson's Table 3). This is in spite of the fact that I do not impose their zero restriction on the response of MP1 to all shocks but one. In spite of my more agnostic approach, the estimation uncertainty is very small. We can conclude that the maximum likelihood estimation that exploits the kurtosis of the data validates these earlier studies and their assumptions.

Another important lesson is that Fed information effects matter, as witnessed by the nontrivial role of u_4, but they manifest themselves as the Delphic forward guidance. The theoretical models of Melosi (2017) and Nakamura and Steinsson (2018) predict information effects that accompany *current* fed fund rate changes, but that is not what shows up in the estimation.

4.3 The distribution of the estimated shocks

Figure 7: The distribution of $\hat{u}$



The marginal distributions of the estimated shocks $\hat{U}$ are very leptokurtic, consistently with the assumed model. Figure 7 shows the histograms of the estimated shocks $\hat{U}$ (blue bars) along with the plots of Student-t densities $\mathcal{T}(0, 1, 1.33)$, with the degrees of freedom parameter $v = 1.33$ that maximizes the likelihood function (red lines). We can see that the Student-t densities match the histograms quite well.

Table 3 reports the correlations between the shocks and, at the same time, illustrates the perils of applying linear statistics to non-Gaussian variables. The rank (Spearman's) correlations, reported in the left panel are all negligible. However, the linear (Pearson's) correlations, reported in the right panel, are sometimes large. Especially striking is the correlation of 0.32 between u_2 (forward guidance shocks) and u_3 (LSAP shocks). Such

Table 3: Rank correlations and linear correlations between the shocks

	Rank correlations					Linear correlations			
	u_1	u_2	u_3	u_4		u_1	u_2	u_3	u_4
u_1	1	-0.01	-0.03	0.03	u_1	1	-0.17	-0.07	-0.12
u_2	(0.83)	1	0.02	0.04	u_2	(0.01)	1	0.32	0.05
u_3	(0.68)	(0.75)	1	0.02	u_3	(0.25)	(0.00)	1	0.02
u_4	(0.66)	(0.53)	(0.80)	1	u_4	(0.06)	(0.48)	(0.76)	1

Note: Correlation coefficients above the diagonal, p-values in parentheses below the diagonal. Rank correlations (Spearman's correlations) in the left panel, linear correlations (Pearsons's correlations) in the right panel. The linear correlation between u_2 and u_3 drops from 0.32 to 0.07 if one omits the QE1 announcement.

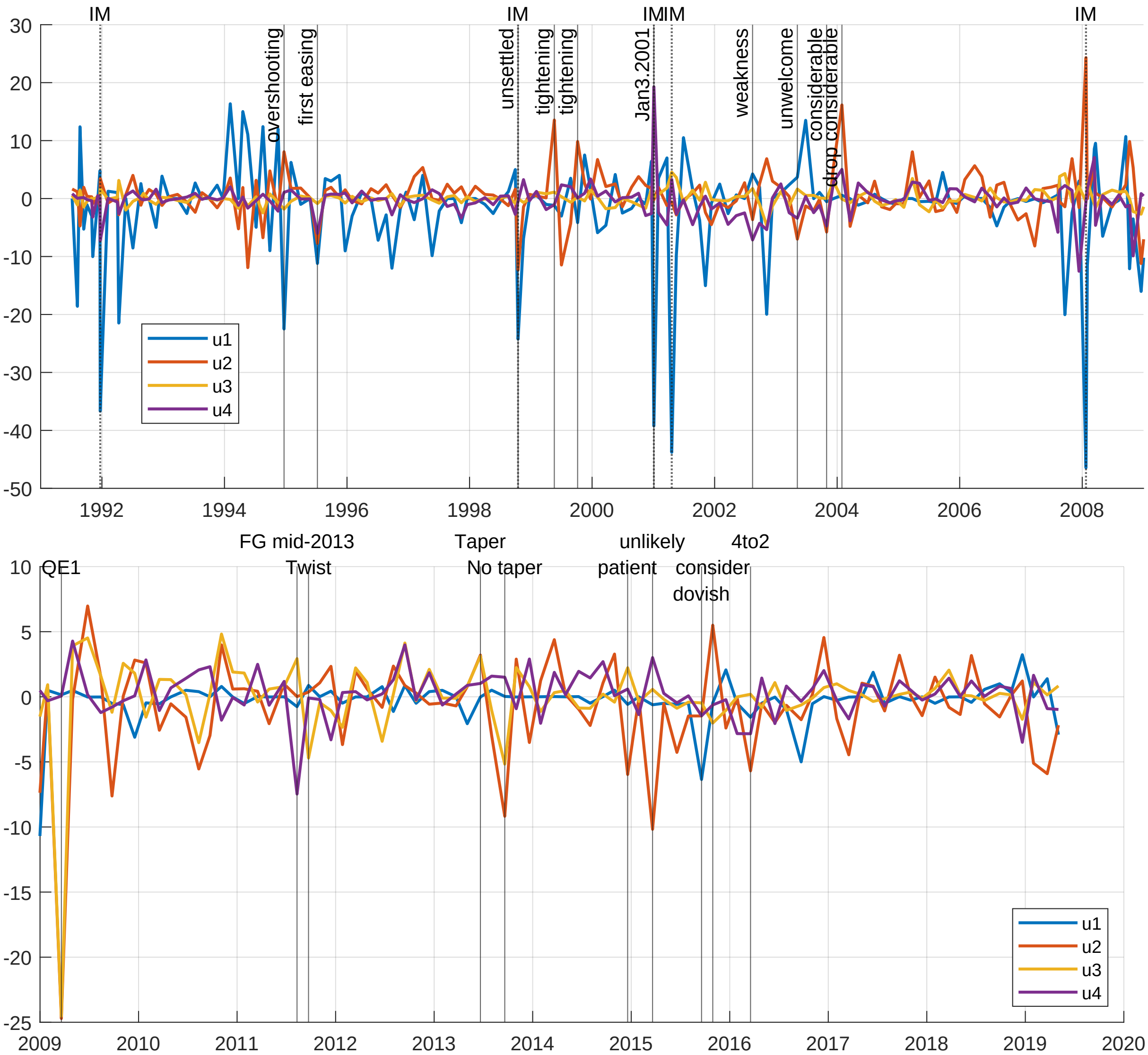
a high correlation between Gaussian shocks would mean that they are systematically related and hence studying their effects in isolation makes little sense. However, for non-Gaussian variables such a high linear correlations can happen by chance. In fact, in this case the linear correlation is almost entirely driven by a single observation, namely the announcement of the QE1 program in March 2009, which caused a particularly large reaction of financial markets. After omitting this single data point the linear correlation drops to 0.07, revealing that the shocks u_2 and u_3 are not in fact systematically linearly related.

4.4 The estimated shocks: the history

Figure 8 reports the history of the shocks over time. To facilitate the interpretation, the shocks are rescaled so that a one unit u_1 shock raises the MP1 by 1 basis point, a one unit u_2 and u_4 raises the ONRUN2 by 1 basis point, and a one unit u_3 shock raises the ONRUN10 by 1 basis point. The top panel of Figure 8 shows the pre-ZLB period 1991-2008 and the bottom panel the remaining period 2009-2019. Vertical bars highlight many of the same events as GSS and Swanson (2020). Appendix B plots the market responses to these events.

The history of the standard monetary policy shock u_1 agrees with the accepted accounts. u_1 is essentially equal to MP1 and is also highly correlated with the GSS target factor/Swanson (2020) fed funds rate shock (rank correlation 0.76, linear correlation 0.95).

Figure 8: The estimated shocks over time.



Note. IM: an "inter-meeting" announcement.

Table 4 reports these and other correlations between various shocks. In the 1991-2008 plot we can see that, as is frequently noted, the largest realizations of standard policy shocks occur at inter-meeting announcements (labeled "IM" in the plot). After 2008 the standard monetary policy shocks are negligible.

The Student-t model interprets some of the forward guidance episodes as Odyssean, u_2 and some as Delphic, u_4, or the mix of both. Table 4 reports that the forward guidance shock of Swanson (2020) is highly positively correlated with both u_2 and u_4 (rank correlations of 0.74 and 0.48 respectively). The 1991-2008 plot in Figure 8 highlights the dates of the ten forward guidance episodes discussed in GSS (their Table 4, "Ten Largest Observations of the Path Factor"). They are labeled with the key word of the FOMC statement or a one-word description of its message. The Odyssean forward guidance, u_2 dominates the announcements marked 'overshooting' (December 1994, markets expect future tightening after Blinder's recent comments of 'overshooting'), 'unsettled' (October 1998), 'tightening' (May and October 1999) and 'drop considerable' (January 2004, dropping of the commitment to a 'considerable period' of the same policy). The Delphic forward guidance u_4 dominates the episodes labeled 'Jan3,2001' and 'weakness' (August 2002). The remaining highlighted announcements ('first easing', 'unwelcome' and 'considerable') are mixtures of both types of forward guidance.

The announcement on January 3, 2001 triggers the largest Delphic shock in the sample. It is a large inter-meeting rate cut that, as discussed in GSS, caused financial markets to mark down the probability or a recession and as a result expect higher rates down the road. The GSS methodology picks it up as a combination of a target factor easing and a path factor (forward guidance) tightening. In this paper's methodology the forward guidance is of the Delphic kind and therefore reinforces the stock market gains rather than dampening them, which helps match the data. Since this u_4 shock is so large, I test the robustness of the results to dropping the January 3, 2001 observation from the sample. The results without this observation are almost unchanged. The correlation of the two estimates of u_4 on the remaining dates is more than 0.99.

In the announcement labeled 'weakness' on August 13, 2002 the FOMC stated that the balance of risks has shifted towards economic weakness. This stimulated both pessimism, reflected in stock market losses, and expectations of lower rates in the future. Therefore, although the announcement did not promise a rate cut explicitly, it worked as a Delphic forward guidance.

In the 2009-2019 plot in Figure 8 the largest Delphic shock is the 'mid-2013' announcement, issued on August 9, 2011, in which the FOMC stated that the near-zero level of the fed funds rate will be appropriate "at least through mid-2013". It is perhaps intuitive that such a date-based forward guidance is prone to trigger a Delphic interpretation. By contrast, the forward guidance episodes from December 2014 to March 2016 are either Odyssean, u_2 or mixes of Delphic and Odyssean.

Interestingly, the 'dovish' announcement on September 17, 2015, which is a major forward guidance shock in Swanson (2020), does not show up as such here. On that day markets priced in some probability that the Fed would raise the rates for the first time since 2008. The Fed did not change the rates and the MP1 dropped by 6.4 basis points upon the announcement. This is interpreted here as a standard fed funds rate shock u_1 of -6.4 basis points, accompanied by a mix of Odyssean and Delphic forward guidance shocks of -1.5 basis points each. However, there are few other so clear discrepancies between the two approaches.

Table 4 shows that the Delphic shock u_4 is highly positively correlated with the central bank information (CBI) shock of Jarociński and Karadi (2020), which picks up the positive correlation between interest rate surprises and stock price surprises. For the baseline CBI shock, which uses the fourth fed funds future (FF4) as the summary of the interest rate surprises, the correlation is 0.58. For the CBI shock based on the first principal component of futures with maturities up to 1 year as the summary of interest rate surprises, (reported by Jarociński and Karadi, 2020 in the Appendix), the correlation is even higher, 0.78.

The largest by far LSAP shock u_3 accompanies the announcement of the expansion of the QE1 program (March 18, 2009). I check the robustness of the results to omitting this observation, but all the lessons remain almost unchanged (see the second line of Table 4). As in Swanson's analysis, this shock is accompanied by a large expansionary Odyssean forward guidance shock. Another sizable expansionary LSAP shock happens at the announcement of the 'Operation Twist' (September 21, 2011). Finally, there is first a contractionary and then an expansionary LSAP shock during the "taper tantrum" episode, the first on June 19, 2013 ('taper') the second on September 18, 2013 ('no taper'). Also consistently with Swanson's findings, there are no expansionary LSAP shocks during the announcements of QE2 and QE3 programs.

4.5 Time variation

Estimation of the model on smaller sub-samples yields two corrections to the previous messages. First, in the earlier part of the sample there is some evidence of the standard information effects associated with the movements of the current fed funds rate (as in Melosi, 2017; Nakamura and Steinsson, 2018). These standard information effects do not

Table 4: Pairwise rank and linear correlations with baseline shocks u_1, u_2, u_3 and u_4

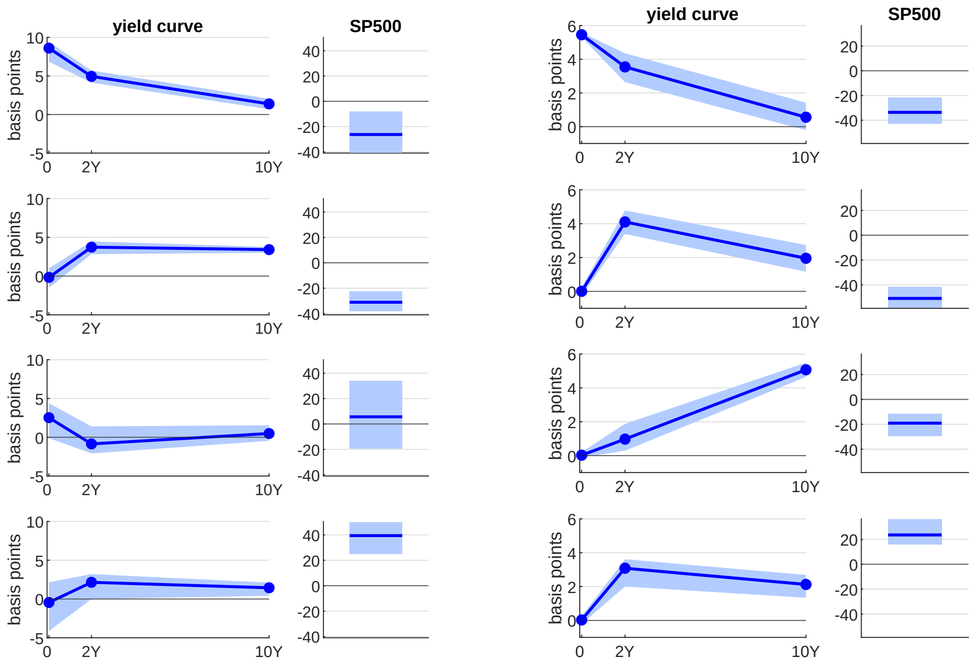
	Obs.		u_1		u_2		u_3		u_4
Changing the sample									
Drop January 3, 2001	239	u_1:	1.000 *(1.000)*	u_2:	0.998 *(0.999)*	u_3:	0.994 *(0.998)*	u_4:	0.998 *(0.999)*
Drop QE1 (March 18, 2009)	239	u_1:	0.998 *(1.000)*	u_2:	0.998 *(0.999)*	u_3:	0.998 *(0.999)*	u_4:	0.997 *(0.999)*
Sample 1999-2004	120	u_1:	0.93 *(0.98)*	u_2:	0.89 *(0.95)*	u_3:	0.91 *(0.94)*	u_4:	0.97 *(0.99)*
Sample 2005-2019	120	u_1:	0.94 *(1.00)*	u_2:	0.82 *(0.78)*	u_3:	0.88 *(0.97)*	u_4:	0.96 *(0.98)*
Other papers									
Swanson (2020)	240	ff:	0.76 *(0.95)*	fg:	0.74 *(0.79)*	lsap:	-0.66 *(-0.84)*	fg:	0.48 *(0.49)*
JK (2020) FF4	221	MP:	0.50 *(0.70)*	MP:	0.62 *(0.44)*	MP:	-0.05 *(-0.03)*	CBI:	0.58 *(0.65)*
JK (2020) 1stPC	237	MP:	0.52 *(0.65)*	MP:	0.69 *(0.56)*	MP:	-0.05 *(0.03)*	CBI:	0.78 *(0.81)*

Note. Rank (Spearman's) correlations on top, regular font; linear (Pearson's) correlations below, in brackets, italics. 'ff', 'fg' and 'lsap' stand for fed funds, forward guidance and large scale asset purchase shocks. 'MP' and 'CBI' stand for monetary policy and central bank information shocks.

replace or modify the Delphic forward guidance but appear as a separate shock substituting the LSAP shock. Second, the LSAP shock u_3 has a significant effect on the stock prices in the later part of the sample.

Figure 9 reports the responses of all variables estimated in the first half of the sample (left panel) and in the second half of the sample (right panel). The error bands in these smaller samples are wider. A number of differences between the left and the right panel show up. First, the standard policy shock is moves the yield curve in a similar way but is larger in the first sample (MP1 increases by 9 basis points) and smaller in the second sample (MP1 increases by less than 6 basis points). Second, in response to the Odyssean forward guidance shock u_2 medium and long rates move in parallel in the first sample, while the effect is hump-shaped in the second sample, with the 10-year rate moving much less. Third, the LSAP shock is non-existent in the first sample. Instead the shock u_3 now resembles the standard information shock associated with the fed funds rate, but

Figure 9: First vs second half of the sample

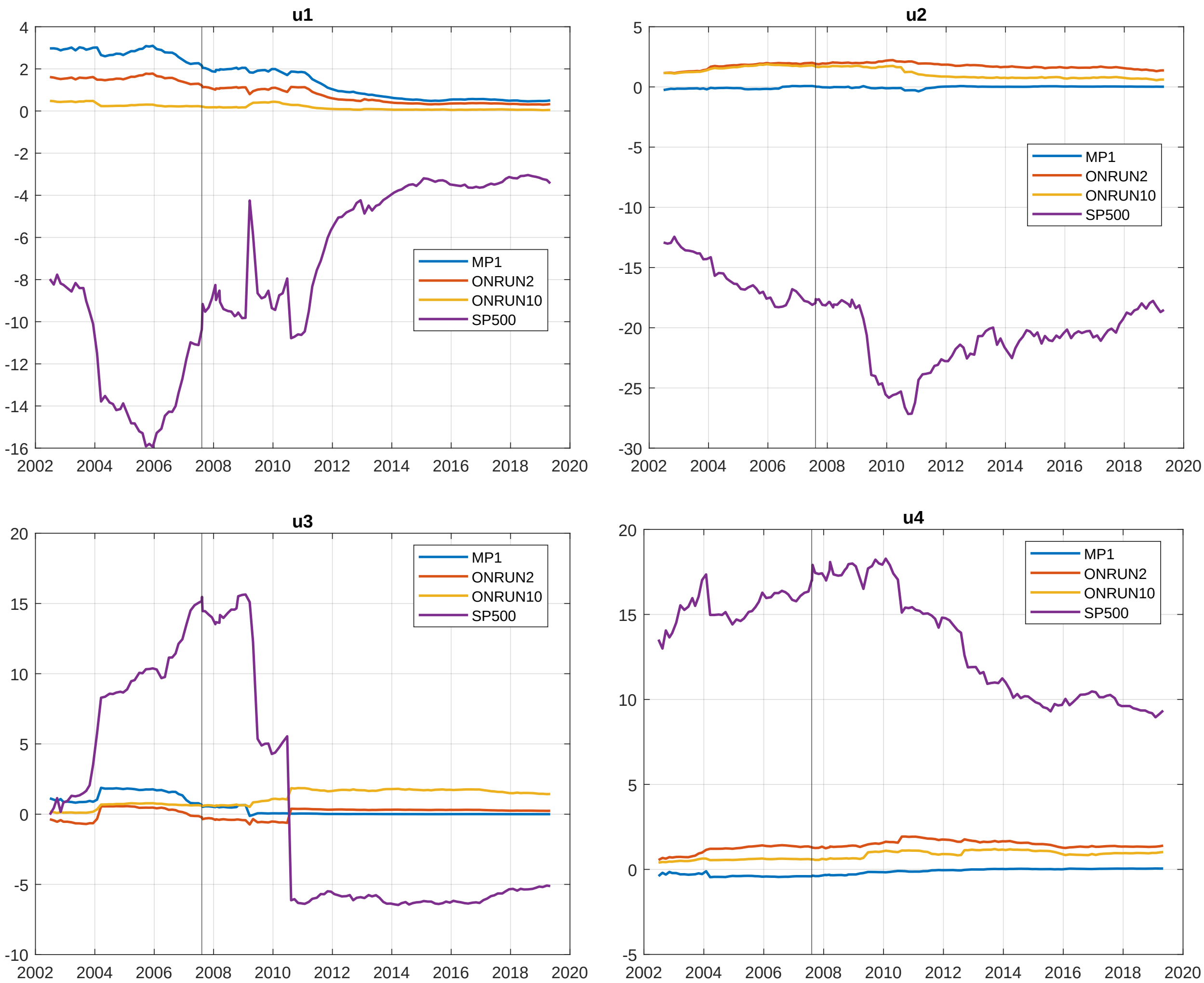


1991-2004 (120 obs.) 2005-2019 (120 obs.)

is not precisely estimated. By contrast, the LSAP shock in the second sample is very pronounced and has a significant and intuitive effect on the stock prices. Finally, the Delphic forward guidance shock is broadly similar but it moves the stock prices more relatively to the interest rates in the first half of the sample.

Figure 10 reports the responses of all variables estimated on rolling windows of 100 observations. Many of these models are imprecisely estimated, but the overall tendencies are clear and quite intuitive. First, the standard monetary policy shock u_1 becomes smaller as the windows include more observations from the ZLB period. Second, for the Odyssean forward guidance u_2 we can see the gradual emergence of the 'hump-shaped' yield curve response noted above. Third, the shock u_3 is unstable and switches from being a standard information shock in the early windows (where it is a fed funds rate hike associated with a positive stock price response) to being a contractionary LSAP shock in the later windows. The switch occurs at the point where the rolling window includes for the first time the QE1 announcement of March 18, 2009. However, the same switch occurs, only several months later, when the QE1 announcement is omitted from the sample. Finally, the Delphic forward guidance shock maintains similar features, while

Figure 10: Rolling window estimates of C



Notes. Each line plots the effect of shock u_i on variable j, $C(i, j)$ estimated on rolling samples of 100 observations. The horizontal axis shows the last observation of the rolling sample. The vertical line shows the beginning of the last sample.

becoming slightly smaller in the later windows.

4.6 Adding variables to the baseline model

This section reports a series of models that include one or more additional variables from the GSS dataset. The four shocks from the baseline model continue to show up in most of these alternative models. The standard monetary policy shock u_1 and the Odyssean forward guidance shock u_2 are remarkably robust and almost always retain their dominant role. On the other hand, the Delphic shock u_4 becomes much smaller (in terms of its impact on the yield curve) in many of the alternative models. The additional shocks that appear in these larger models are either best described as idiosyncratic shocks to individual variables, as variants of the baseline shocks, or are imprecisely estimated and difficult to interpret economically.

Figure 11: Adding a short-term interest rate instrument

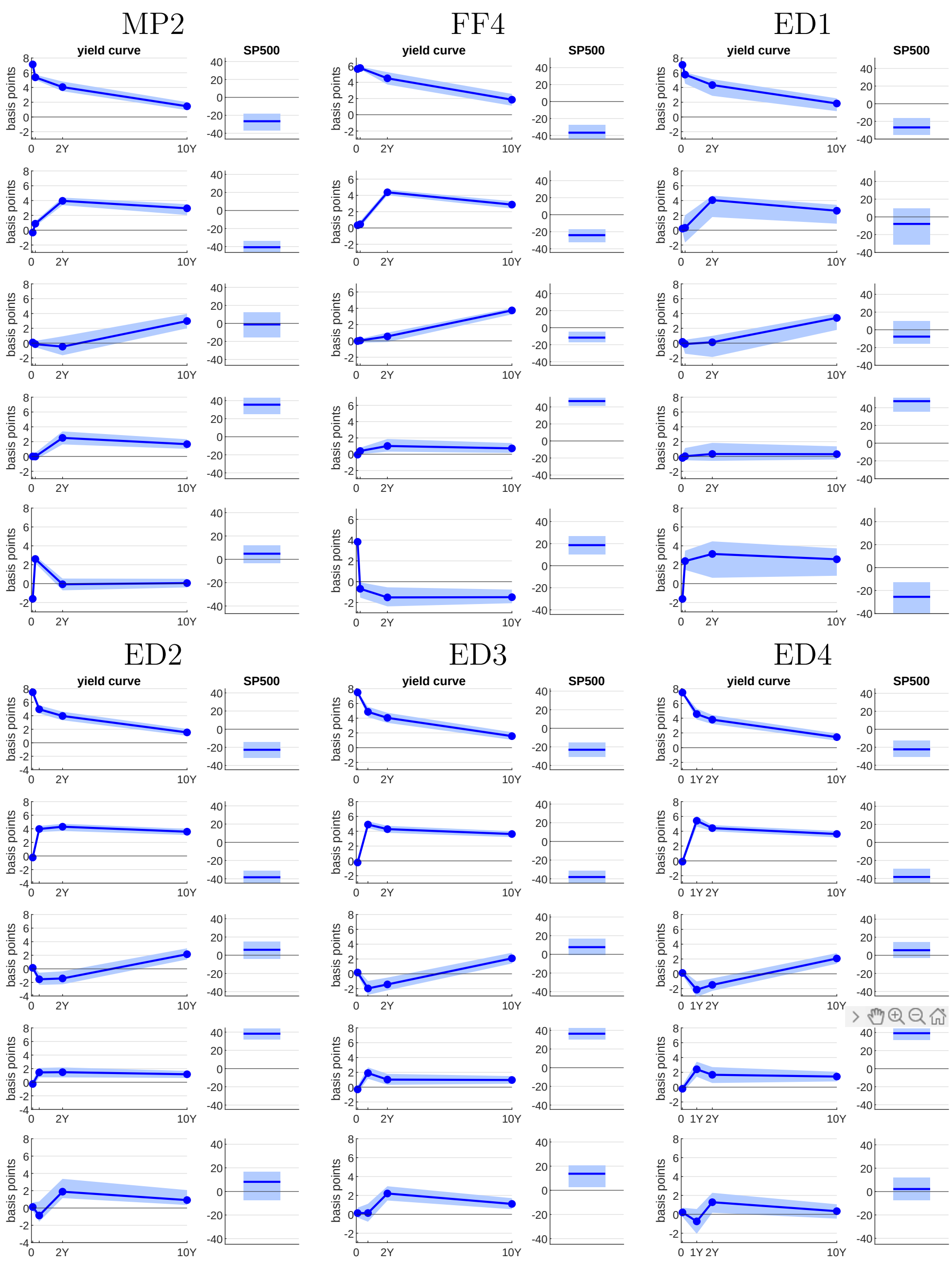


Figure 12: Adding other variables

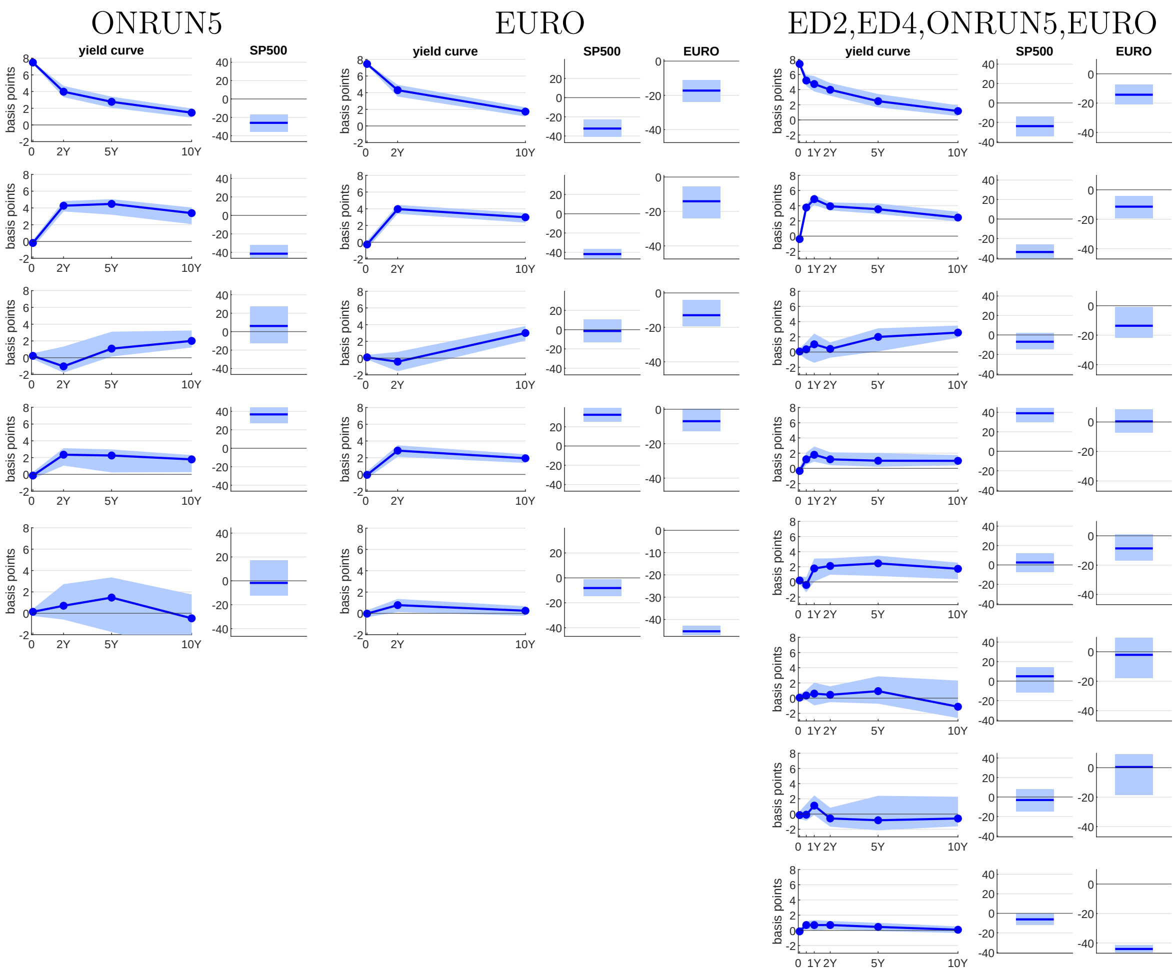


Figure 11 reports models with additional interest rates instruments with maturities under two years. MP2 is the fed funds rate expected after the second FOMC meeting (constructed by GSS from the fed funds futures). The additional shock captures the idiosyncratic variation in MP2. FF4 is the fourth fed funds future, which has a maturity of three months. The additional shock is a sizable (4 basis points) fed funds rate hike accompanied by an expectation of lower rates in the future and triggering a stock price increase. ED1 is the first eurodollar future, which expires at the end of the quarter. The additional shock is similar to the one in the FF4 model, but with an only two basis point movement in the fed funds rate. ED2 is the second eurodollar future, which expires at the end of the following quarter. The additional shock involves a significant movement of

Table 5: Pairwise rank correlations with the baseline model shocks

	Obs.		u_1		u_2		u_3		u_4
Models in Figure 11									
the model with MP2	240	u_1:	0.871	u_2:	0.984	u_3:	0.995	u_4:	0.987
FF4	240	u_1:	0.650	u_2:	0.597	u_3:	0.952	u_4:	0.891
ED1	240	u_1:	0.887	u_2:	0.636	u_3:	0.983	u_4:	0.785
ED2	240	u_1:	0.988	u_2:	0.981	u_3:	0.973	u_4:	0.849
ED3	240	u_1:	0.986	u_2:	0.963	u_3:	0.952	u_4:	0.750
ED4	240	u_1:	0.980	u_2:	0.994	u_3:	0.951	u_4:	0.969
Models in Figure 12									
ONRUN5	240	u_1:	0.987	u_2:	0.999	u_3:	0.941	u_4:	0.996
EURO	240	u_1:	0.997	u_2:	0.945	u_3:	0.968	u_4:	0.998
ED2,ED4,ONRUN5,EURO	240	u_1:	0.967	u_2:	0.927	u_3:	0.919	u_4:	0.869

Note. The first column identifies models by the variable(s) added to the baseline specification.

only the 2-year and 10-year treasury yields. With ED3 the additional shock is similar, but with a significant positive response of the stock prices, making it a second, more longer term Delphic forward guidance shock. With ED4 the additional shock is only significant for the 2-year treasury yield. In all these models the effect of the baseline Delphic shock u_4 on the yield curve is diminished, and with ED2 it becomes completely insignificant. Furthermore, in the models with ED2, ED3 and ED4 the LSAP shock that raises the 10-year yield has a significantly negative impact on the respective eurodollar future and the 2-year Treasury yield.

Figure 12 reports three additional models. ONRUN5 is the 5-year Treasury yield. The additional shock affects mainly the 5-year Treasury yield itself, but is imprecisely estimated. EURO is the exchange rate, in US dollars per euro. The exchange rate appreciates after all the four baseline shocks, consistently with the uncovered interest rate parity. The additional shock captures the idiosyncratic movements in the exchange rate not explained by the other shocks. Finally, the last model adds four variables: second and fourth eurodollar futures (ED2,ED4), five-year Treasury yield (ONRUN5) and the dollar/euro exchange rate (EURO). Shocks u_1 and u_2 are remarkably robust also in this large model. The LSAP shock is similar to the baseline model, though less precisely estimated. The Delphic forward guidance shock is also similar to the baseline but, as in most of the larger models, its impact on the yield curve is smaller, almost halved. The first additional shock is a parallel shift of the yield curve with no significant effect on the stock prices (thus, it could be a combination of an Odyssean and a Delphic forward guidance). The next two shocks are imprecisely estimated. The last shock is the idiosyncratic exchange rate shock familiar from the previous model.

Table 5 reports the rank correlations of the first four shocks from the models reported in Figures 11 and 12 with the four baseline shocks. These correlations tend to be quite high.

One lesson from these exercises is that there seems to be a need for variable-specific idiosyncratic shocks along with the pervasive and economically interpretable shocks. Models combining non-Gaussian shocks and a factor structure may be a promising way forward.

5 Longer term effects: daily local projections

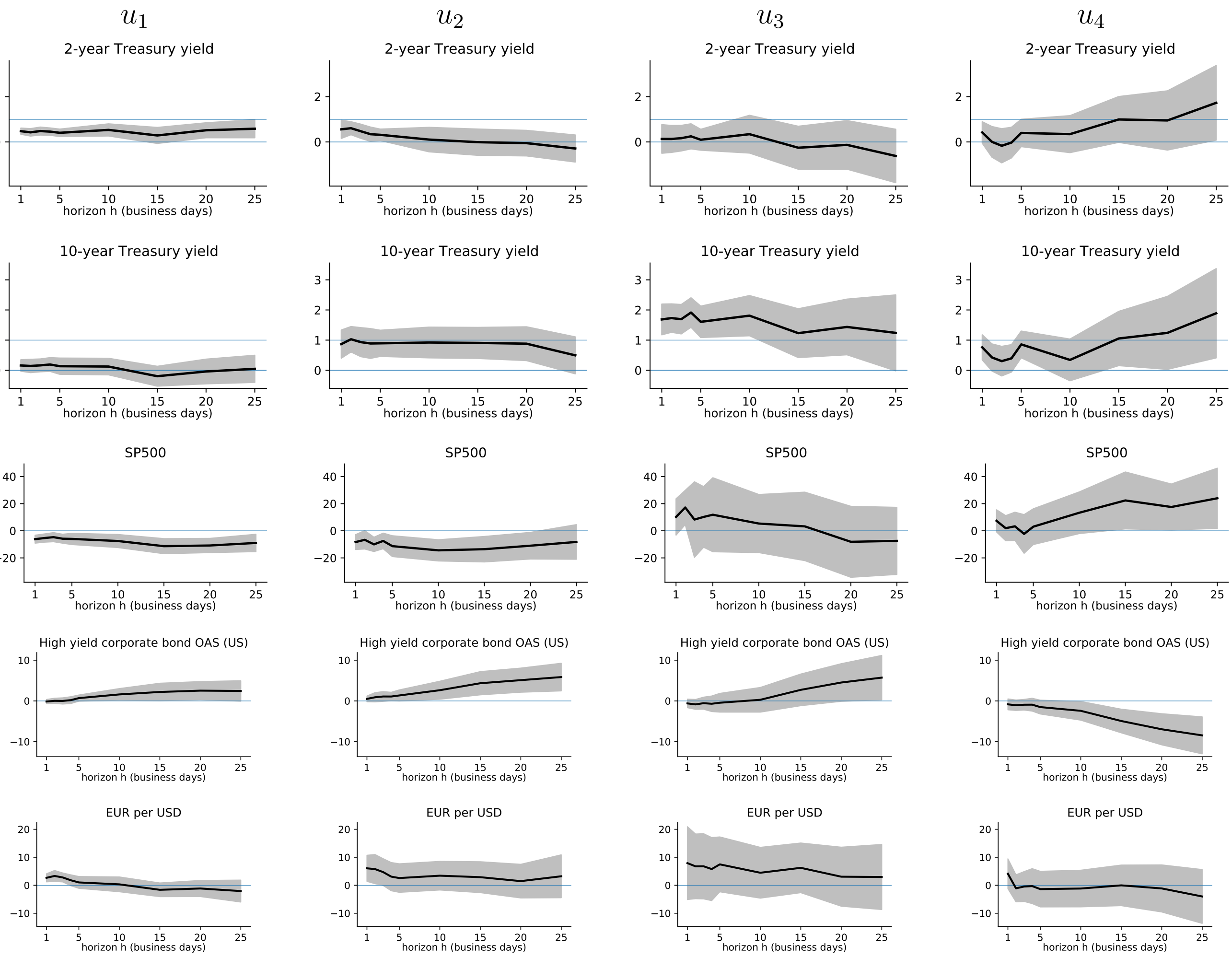
To study the effects of the four baseline shocks beyond the first thirty minutes after the FOMC announcement I estimate local projections:

$$x_{t+h} - x_{t-1} = \alpha + \beta_h^i u_{i,t} + e_t, \tag{7}$$

where x_t is a daily financial variable and t is day of the FOMC announcement. I consider horizons $h = 1, 3, 5, 10, 15, 20, 25$ business days. $u_{i,t}, i = 1, 2, 3, 4$ are the maximum likelihood estimates of the shocks implied by the baseline model above, rescaled so that a one unit u_1 shock raises the MP1 by 1 basis point, a one unit u_2 and u_4 raises the ONRUN2 by 1 basis point, and a one unit u_3 shock raises the ONRUN10 by 1 basis point. The shocks are included in the regressions one-by-one. β_h^i is the quantity of interest: the effect of a one unit shock. I estimate equation (7) with OLS and compute heteroskedasticity-consistent errors. Figure 13 reports the results.

Three main lessons follow from these local projection results. First, the effects of the shocks on interest rates and stock prices in the first 30 minutes given by the matrix C are not just temporary blips. They persist in the following days and weeks, and are statistically significant at many, though not all horizons. In particular, shocks u_1 and

Figure 13: The effects of the shocks on daily financial variables: local projections



Note. The variables are in the same units as the shocks. 90% bands (+/-1.645 standard deviations)

u_2 significantly increase the 2-year Treasury yield (with the elasticity of approximately 0.5) and depress the stock prices (with the elasticities of -6 and -8). Shocks u_2 and u_3 significantly increase the 10-year Treasury yields (with the elasticities of 1 and almost 2). The positive effect of the Delphic shock u_4 on Treasury yields and stock prices is marginally significant at some horizons and insignificant at others.

Second, the shocks gradually propagate through the financial system and with some delay get reflected in the corporate bond spreads. Especially the Odyssean forward guidance shock u_2 significantly increases the corporate bond spreads after a few weeks. The effect of standard monetary policy u_1 and asset purchases u_3 on the corporate bond spread is also positive but only marginally significant. The Delphic shock u_4 strongly and significantly reduces the corporate bond spreads.

Third, the standard policy and forward guidance shocks u_1 and u_2 significantly strengthen the dollar vs the euro (with the elasticities of 3 and 6 respectively). The effect of the asset purchase shock u_3 is even larger according to the point estimates (the elasticity of 8), but estimated with a large uncertainty. The effect of the Delphic shock u_4 on the dollar is the weakest, it is actually zero at most horizons. This shock's weak impact on the exchange rate is consistent with the recently highlighted role of the dollar as a key barometer of financial market risk-taking capacity (Avdjiev et al., 2019). A positive Delphic shock increases the financial markets' appetite for risk and this pushes the dollar down, in practice roughly canceling any effect of higher US interest rates.

6 Even longer term effects: putting the shocks in a monthly VAR

This section studies the longer term effects of the Fed policy shocks using Bayesian VARs with monthly variables. I estimate four monthly VARs, one for each shock. I aggregate each shock $u_i, i = 1, ..., 4$ to the monthly frequency by adding them up. The resulting variables are zero in the months without FOMC announcements. The vector of variables consists of: u_i, 1-year Treasury yield, 10-year Treasury yield, S&P500, Excess Bond Premium (EBP) of Gilchrist and Zakrajsek (2012), Industrial Production, CPI. I place the shock u_i first and identify the VAR recursively (i.e. with the Choleski decomposition).

6.1 Estimation of a VAR with (at least) one Student-t shock

When estimating the VAR I account for the fact that the shocks u_i are Student-t. In all other dimensions the VAR is standard. In particular, the remaining shocks are assumed to be Gaussian, as is common practice, and I use standard Minnesota-type priors.

The joint density of Student-t and Gaussian variables does not in general exist in closed form, so I model it using data augmentation. This approach exploits the fact that if q is a χ^2 variable with v degrees of freedom and $z \sim \mathcal{N}(0, 1)$ then $\sqrt{\frac{v}{q}}z$ has the Student-t distribution with v degrees of freedom. It follows that a vector (w_1, w_2) constructed as

$$w_1 = \sqrt{\frac{v}{q}} c_1 z_1, \qquad w_2 = c_2 z_1 + c_3 z_2, \tag{8}$$

where c_1, c_2, c_3 are known constants, has a joint distribution such that w_1 and w_2 are correlated, the marginal distribution of w_1 is Student-t and the marginal distribution of w_2 is Gaussian. Such joint distributions are discussed in Jones (2002); Shaw and Lee (2008). Beyond bivariate cases they have no closed form representations, but can still be handled using data augmentation, i.e. treating q as an unobserved variable that is estimated together with the other parameters (Geweke, 1993). In particular, the mixed t and normal distribution I use here is a special case of the Non-Elliptically Contoured Multivariate t Distribution (Jiang and Ding, 2016).

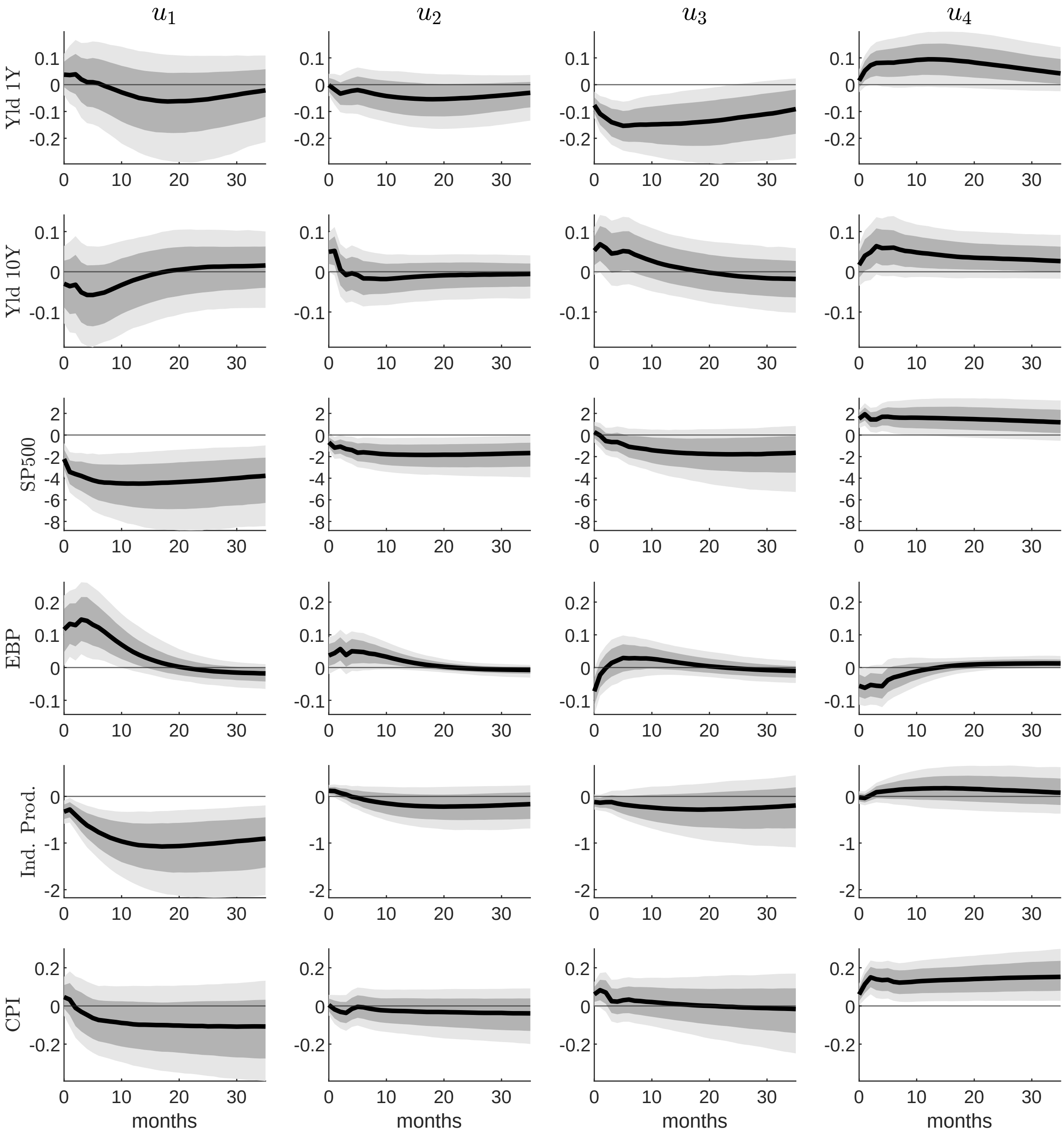
The VAR model is

$$y_t = B_1 y_{t-1} + ... + B_P y_{t-P} + b_0 + Q_t^{-1/2} e_t, \qquad e_t \sim \mathcal{N}(0, \Sigma), \tag{9}$$

where $Q_t = \text{diag}(q_t/v, 1, ..., 1)$ and the prior for q_t is $\chi^2(v)$. The effect of introducing Q_t is similar to a Generalized Least Squares estimation, in which the observations with large realizations of u_i are weighed down, compared with the standard Gaussian VAR without the Q_t. In the standard Gaussian VAR these observations would have an unduly large influence on the estimates.

The prior for $b_0, B_1, ..., B_P, \Sigma$ is a standard Minnesota-type prior, following Litterman (1979). The prior is specified as an independent Normal-Inverted Wishart distribution and I use standard hyperparameter values ("overall tightness" 0.2, "decay" 1 and the one unit root and no-cointegration dummy observation priors with weight 1 each). The prior mean of the first own lag of u_i is zero and it is 1 for the other variables. The VAR has 6 lags. I simulate the posterior with the Gibbs sampler, with a Metropolis step for q_t. I fix the degrees of freedom parameter v of the χ^2 at 4 (it would be a simple extension to specify a prior for it and estimate it as well).

Figure 14: Impulse responses. VAR with one Student-t shock.

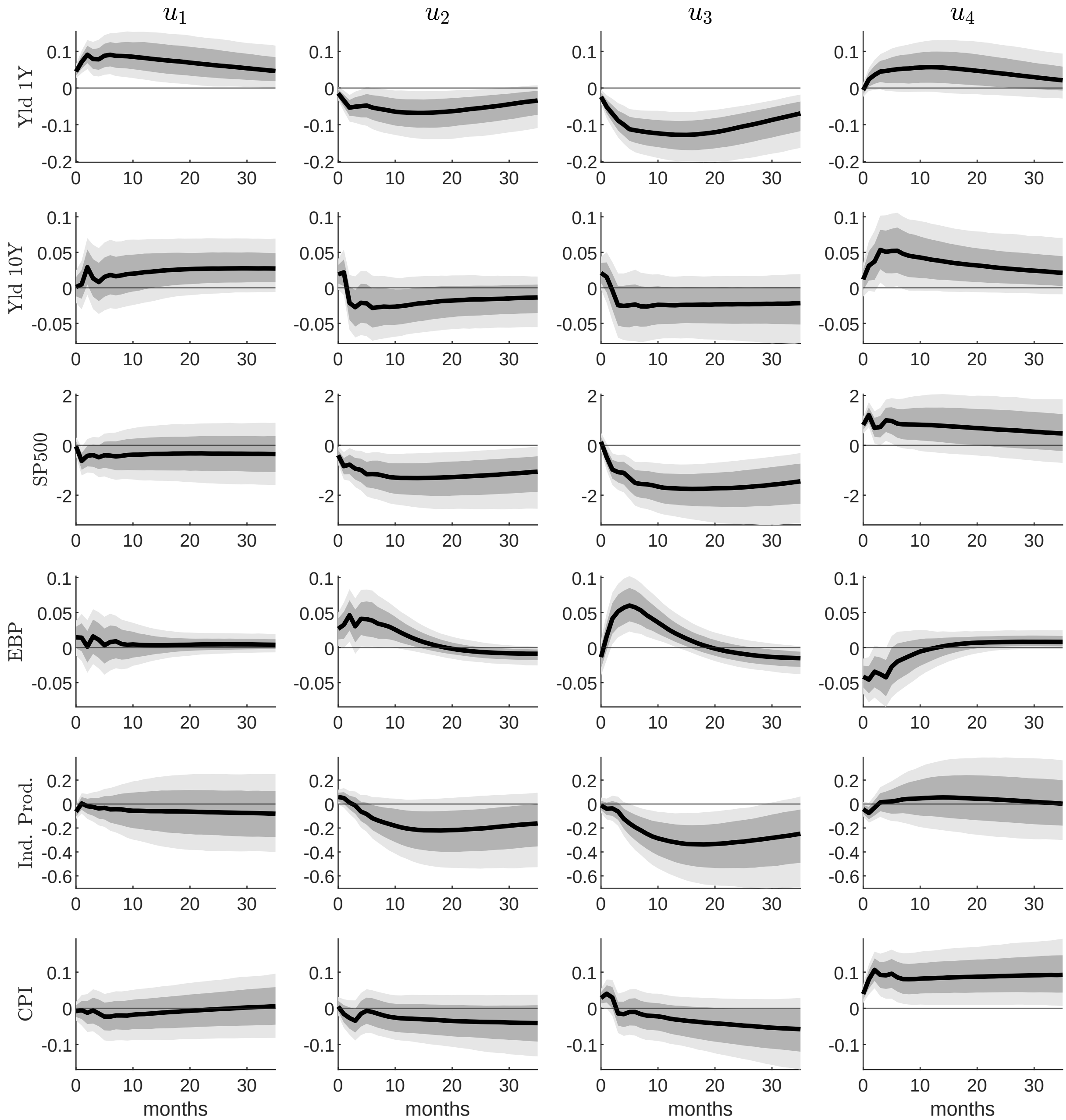


Note: Impulse responses to one basis point shocks. All the variables are in percent. The solid lines are the median impulse responses, the darker grey areas are the 16-84 percentile bands and the lighter grey areas are the 5-95 percentile bands. The figure is based on 10,000 draws from the Gibbs sampler.

6.2 Impulse responses of the monthly variables

The VAR impulse responses reported in Figure 14 yield two main lessons. First, the monetary policy shock u_1 has the most significant effects on the financial markets and the

Figure 15: Impulse responses. Gaussian VAR.



Note: Impulse responses to one basis point shocks. All the variables are in percent. The solid lines are the median impulse responses, the darker grey areas are the 16-84 percentile bands and the lighter grey areas are the 5-95 percentile bands. The figure is based on 2,000 draws from the posterior.

economy, and the strongest effects per one basis point shock, The effects of the forward guidance shock u_2 and the asset purchases shock u_3 are smaller, similar in size and less precisely estimated. The Delphic forward guidance shock has a significant expansionary effect.

Second, comparing Figure 14 with Figure 15 we can see that the non-Gaussianity of the shocks matters for the estimation. In particular, under the (false) assumption that the shocks are Gaussian, the effects of the unconventional policy shocks u_2, u_3 are much stronger and those of u_1 are smaller and cease to be significant.

More in detail, a one basis point monetary policy shock u_1 is followed by the decline of the S&P500 index by about 2% and an increase of the excess bond premium by about 12 basis points. Industrial production gradually contracts by 1 percent and the CPI gradually declines by about 10 basis points, though this last effect is not very significant. The median effect of the 1 basis point shock on the monthly 1-year Treasury yield is about 3 basis points but very imprecisely estimated. These results turn around if we mistakenly treat the shock as Gaussian. In this case its effect on the 1-year Treasury yield is slightly larger (5 basis points) and appears extremely sharply estimated. However, the responses of the EBP and S&P500 become much smaller and the responses of industrial production and prices basically disappear.

The forward guidance shock u_2 and the asset purchase shock u_3 have a broadly similar contractionary effect. Monthly 1-year Treasury yields are not significantly affected after u_2 and even fall after u_3, but the 10-year Treasury yields increase by about 5 basis points after 1-basis-point shocks of both kinds. Stock prices fall by about 1-2 percent in the medium run. The forward guidance shock u_2 increases the EBP by about 4 basis points. After the asset purchase shock the impact response of the EBP is negative, but it becomes positive in the medium run. Industrial production gradually falls by about 15 basis points. The responses of CPI inflation are insignificantly different from zero, except for a short-lived price puzzle after u_3.

Finally, a one basis point Delphic forward guidance shock u_4 increases the 1-year and 10-year Treasury yields by about 1-2 basis points on impact and more in the subsequent months. It increases the S&P500 by 2 percent and decreases the EBP by almost 5 basis points. The CPI consumer price index increases by about 15 basis points within a few months and industrial production by about 5 basis points (though this effect is not significant). These effects are qualitatively similar to the effects of the Central Bank Information shock reported in Jarociński and Karadi (2020). They are also quite similar in Figures 14 and 15, implying that the findings about this shock, unlike the other three shocks, do not depend much on treating the shock as Gaussian or fat-tailed.

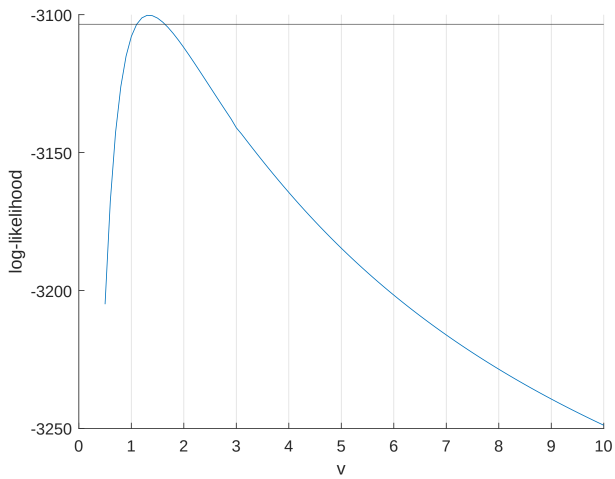
7 Conclusions

This paper exploits the high kurtosis of financial market responses to pin down four main dimensions of FOMC announcements, which can be naturally labeled as: standard monetary policy, Odyssean forward guidance, LSAP and Delphic forward guidance. These shocks have plausible effects on financial markets and provide intuitive interpretations of the FOMC announcements in the sample. The findings on the FOMC policies and their effects are consistent with the well-known studies of GSS and Swanson (2020), in spite of not using their assumptions, thus providing their independent validation. This paper additionally refines these studies by accounting also for the Delphic announcements. The shocks have plausible effects in a VAR with standard macroeconomic variables.

Appendix A Sensitivity of the baseline model to the distributional assumptions

The results remain very similar for values of v between 1 and 10. For $v > 10$ the identification becomes weaker and the point estimates begin to change. However, even values much smaller than 10 are strongly rejected in favor of the point estimate $v = 1.33$.

Figure A.1: Maximum log-likelihood conditional on different values of v

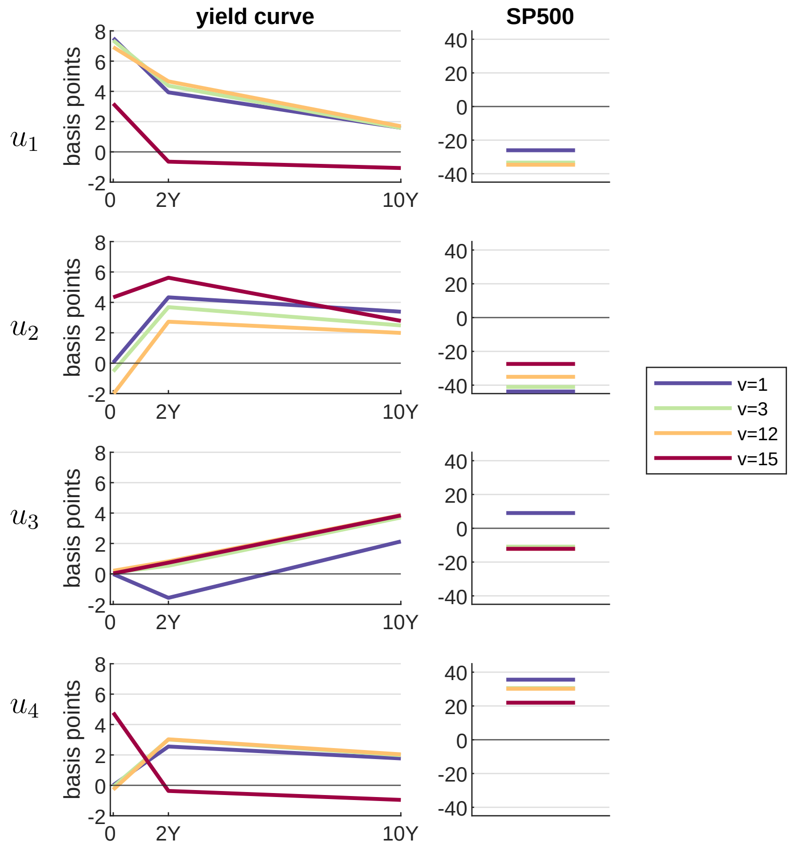


Note. The horizontal line shows the cut-off point implied by the likelihood ratio test at the 1% significance level.

To examine the sensitivity of the results to v I re-estimate model (4) fixing v at a grid of values from 0.5 to 30. Figure A.1 shows that the maximum attainable value of the log-likelihood decreases quickly as v deviates from the unconstrained estimate of 1.33. The figure is truncated at $v = 10$ for readability but the log-likelihood continues to decrease also for $v > 10$. The horizontal line at the top of the figure shows the cut-off point implied by the likelihood ratio test at the 1% significance level. We can see that already the null hypothesis of $v = 2$ is rejected.

Figure A.2 shows that the effects of the four shocks are very similar for values of v from 1 to 12. Especially for the shocks u_1 and u_4 the estimates are difficult to distinguish in the figure as they lie almost on top of each other. The main visible difference is present for long-term rate shocks u_3: its effect on the 2-year yield is slightly negative for low v and becomes positive starting at about $v = 3$. The point estimates change qualitatively

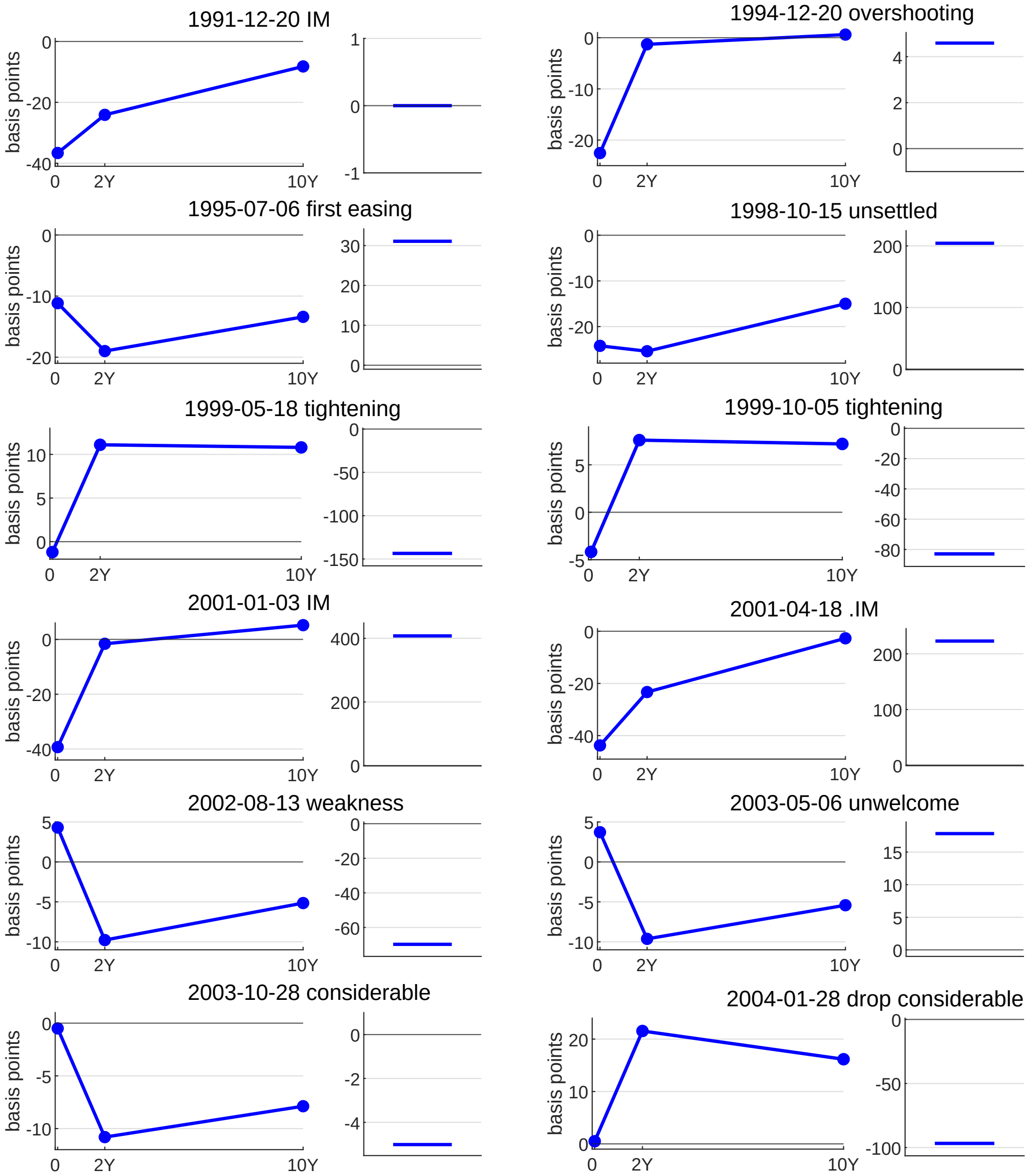
Figure A.2: The effects of standardized shocks, conditional on different values of v



somewhere between $v = 12$ and $v = 15$: shocks u_1 and u_4 become essentially fed funds rate shocks with little effect on the longer maturities, while u_2 becomes an almost parallel shift of the whole yield curve including the shortest maturity. However, for $v = 15$ the uncertainty is substantially larger and many effects are no longer statistically significant (the same is true for $v = 12$, but not for $v \leq 10$).

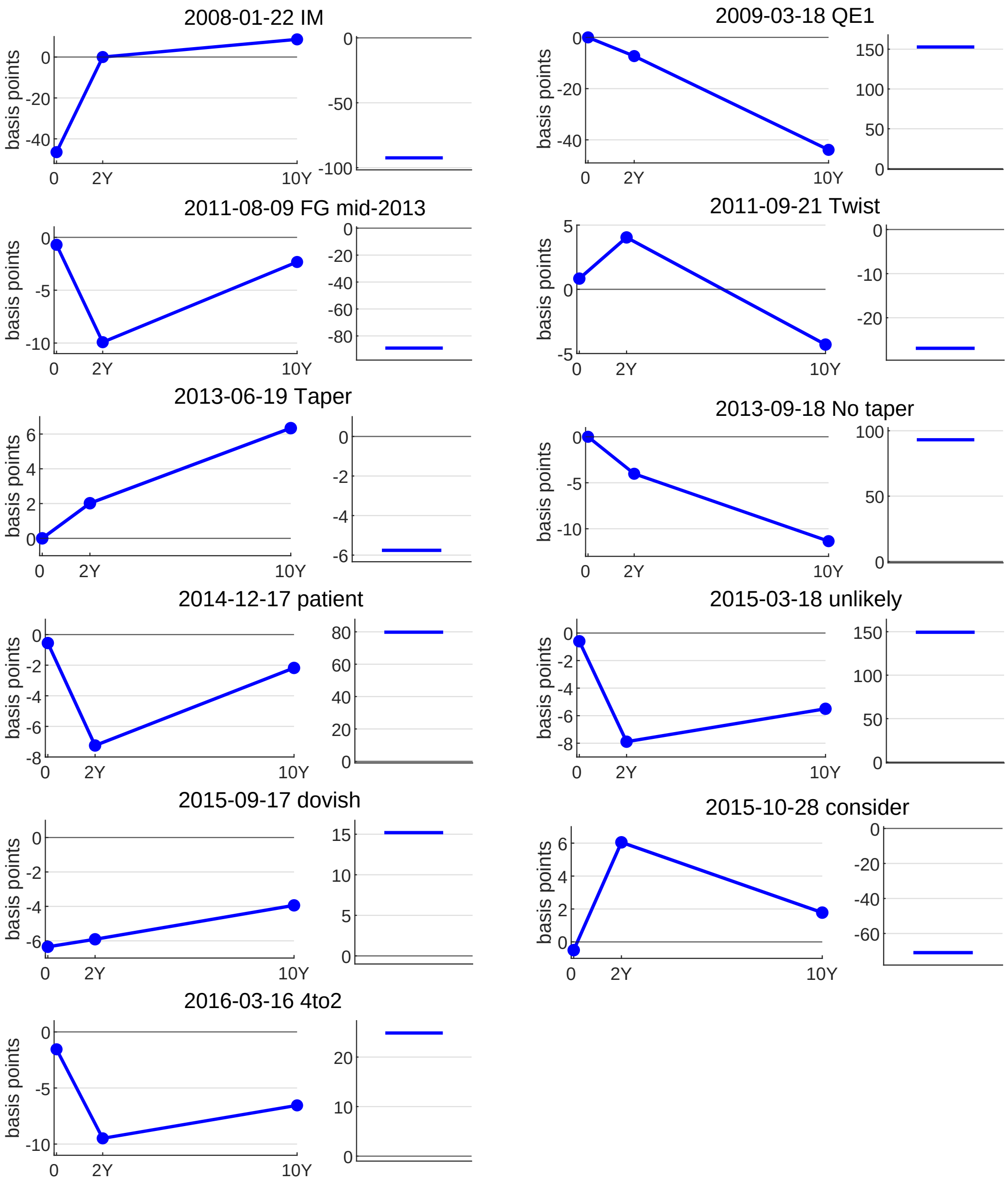
Appendix B Additional figures

Figure B.1: The effects of selected FOMC announcements before 2008



Note. The horizontal line in the right subplots represents the change of the S&P500 stock index. IM stands for an "inter-meeting" announcement.

Figure B.2: The effects of selected FOMC announcements since 2008



Note. The horizontal line in the right subplots represents the change of the S&P500 stock index.

References

Avdjiev, Stefan, Wenxin Du, Cathérine Koch, and Hyun Song Shin (2019) "The Dollar, Bank Leverage, and Deviations from Covered Interest Parity," *American Economic Review: Insights*, 1 (2), 193–208, 10.1257/aeri.20180322.

Baumeister, Christiane and James D. Hamilton (2015) "Sign Restrictions, Structural Vector Autoregressions, and Useful Prior Information," *Econometrica*, 83 (5), 1963–1999, 10.3982/ECTA12356.

Bernanke, Ben S. and Kenneth N. Kuttner (2005) "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *The Journal of Finance*, 60 (3), 1221–1257, 10.1111/j.1540-6261.2005.00760.x.

Bonhomme, Stephane and Jean-Marc Robin (2009) "Consistent noisy independent component analysis," *Journal of Econometrics*, 149 (1), 12–25, 10.1016/j.jeconom.2008.12.019.

Braun, Robin (2021) "The importance of supply and demand for oil prices: evidence from non-Gaussianity,"Technical report, Bank of England.

Brunnermeier, Markus, Darius Palia, Karthik A. Sastry, and Christopher A. Sims (2020) "Feedbacks: Financial Markets and Economic Activity," *American Economic Review*, forthcoming, `https://ideas.repec.org/p/pri/cepsud/257.html`.

Campbell, Jeffrey R., Charles L. Evans, Jonas D. M. Fisher, and Alejandro Justiniano (2012) "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 1–80, `https://EconPapers.repec.org/RePEc:bin:bpeajo:v:43:y:2012:i:2012-01:p:1-80`.

Cieślak, Anna and Andreas Schrimpf (2019) "Non-monetary news in central bank communication," *Journal of International Economics*, 118, 293–315, 10.1016/j.jinteco.2019.01.012.

Comon, Pierre (1994) "Independent component analysis, A new concept?" *Signal Processing*, 36 (3), 287 – 314, 10.1016/0165-1684(94)90029-9.

Geweke, John (1993) "Bayesian treatment of the independent Student-t linear model," *Journal of Applied Econometrics*, 8 (S1), S19–S40, 10.1002/jae.3950080504.

Giacomini, Rafaella and Toru Kitagawa (2020) "Robust Bayesian inference for set-identified models," *Econometrica*, forthcoming.

Gilchrist, Simon and Egon Zakrajsek (2012) "Credit Spreads and Business Cycle Fluctuations," *The American Economic Review*, 102 (4), 1692–1720, 10.1257/aer.102.4.1692.

Gouriéroux, Christian, Alain Monfort, and Jean-Paul Renne (2017) "Statistical inference for independent component analysis: Application to structural VAR models," *Journal of Econometrics*, 196 (1), 111 – 126, https://doi.org/10.1016/j.jeconom.2016.09.007.

——— (2020) "Identification and Estimation in Non-Fundamental Structural VARMA Models," *The Review of Economic Studies*, 87 (4), 1915–1953, 10.1093/restud/rdz028.

Gürkaynak, Refet S., Brian Sack, and Eric Swanson (2005) "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1 (1), 55–93, https://ideas.repec.org/a/ijc/ijcjou/y2005q2a2.html.

Hyvärinen, Aapo, Juha Karhunen, and Erkki Oja (2001) *Independent Component Analysis*: Wiley.

Inoue, Atsushi and Barbara Rossi (2018) "A new approach to measuring economic policy shocks, with an application to conventional and unconventional monetary policy," Economics Working Papers 1638, Department of Economics and Business, Universitat Pompeu Fabra, https://ideas.repec.org/p/upf/upfgen/1638.html.

Jarociński, Marek and Peter Karadi (2020) "Deconstructing Monetary Policy Surprises - The Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12 (2), 1–43, 10.1257/mac.20180090.

Jiang, Zhichao and Peng Ding (2016) "Robust modeling using non-elliptically contoured multivariate t distributions," *Journal of Statistical Planning and Inference*, 177, 50–63, 10.1016/j.jspi.2016.04.004.

Jones, M.C. (2002) "A dependent bivariate t distribution with marginals on different degrees of freedom," *Statistics & Probability Letters*, 56 (2), 163–170, 10.1016/S0167-7152(01)00180-8.

Kuttner, Kenneth N. (2001) "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47 (3), 523–544, 10.1016/S0304-3932(01)00055-1.

Lanne, Markku, Mika Meitz, and Pentti Saikkonen (2017) "Identification and estimation of non-Gaussian structural vector autoregressions," *Journal of Econometrics*, 196 (2), 288 – 304, 10.1016/j.jeconom.2016.06.002.

Lewis, Daniel J. (2019) "Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Macroeconomic Effects," Staff Reports 891, Federal Reserve Bank of New York, `https://ideas.repec.org/p/fip/fednsr/891.html`.

——— (2020) "Robust Inference in Models Identified via Heteroskedasticity," *Review of Economics and Statistics*, forthcoming, 10.1162/rest_a_00963.

Litterman, Robert B. (1979) "Techniques of Forecasting Using Vector Autoregressions," `http://ideas.repec.org/p/fip/fedmwp/115.html`, Federal Reserve Bank of Minneapolis Working Paper number 115.

Melosi, Leonardo (2017) "Signalling Effects of Monetary Policy," *The Review of Economic Studies*, 84 (2), 853–884, 10.1093/restud/rdw050.

Miranda-Agrippino, Silvia and Giovanni Ricco (2020) "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, `https://www.aeaweb.org/articles?id=10.1257/mac.20180124`, forthcoming.

Nakamura, Emi and Jón Steinsson (2018) "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *The Quarterly Journal of Economics*, 133 (3), 1283–1330, 10.1093/qje/qjy004.

Rigobon, Roberto (2003) "Identification Through Heteroskedasticity," *The Review of Economics and Statistics*, 85 (4), 777–792, 10.1162/003465303772815727.

Shaw, William T. and K.T.A. Lee (2008) "Bivariate Student t distributions with variable marginal degrees of freedom and independence," *Journal of Multivariate Analysis*, 99 (6), 1276 – 1287, 10.1016/j.jmva.2007.08.006.

Swanson, Eric T. (2020) "Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets," *Journal of Monetary Economics*, 10.1016/j.jmoneco.2020.09.003, forthcoming.

Waggoner, Daniel F. and Tao Zha (2003) "Likelihood preserving normalization in multiple equation models," *Journal of Econometrics*, 114 (2), 329–347, 10.1016/S0304-4076(03)00087-3.