

Estimating the Fed’s Unconventional Policy Shocks*

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January 5, 2024

Abstract

Financial market responses to Fed monetary policy announcements are often very small, but sometimes very large and the mix of news contained in these announcements varies over time. I exploit these features of the data to estimate different types of Fed policy shocks. The resulting shocks can be naturally labeled as standard monetary policy, Odyssean forward guidance, large scale asset purchases and Delphic forward guidance. They affect risk-free interest rates, stock prices and the dollar on impact and have delayed but pronounced effects on corporate bond spreads and breakeven inflation rates.

Keywords: High-frequency identification, Non-Gaussianity, Fat tails, Forward guidance, Asset purchases

JEL classification: E52, E58, E44

1 Introduction

Modern central banks deploy a variety of policies in their efforts to steer the economy and measuring the effects of these different policies is of paramount importance for monetary economics. Since [Kuttner \(2001\)](#), many papers identify monetary policy shocks from 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 on the state of the economy and the Fed’s expected response to it. Afterwards, asset prices incorporate also any unexpected news conveyed in the announcement. These news could be about the current fed funds rate or its future path, asset purchases, the Fed’s view on the state of the economy, etc. They represent different structural shocks that may affect the economy differently, so it is crucial to disentangle their effects.

This paper estimates the structural shocks that underlie the financial market reactions to FOMC announcements. While the nature of the shocks is not specified *ex ante*, *ex*

*The opinions in this paper are those of the author and do not necessarily reflect the views of the European Central Bank. I thank anonymous referees, Jesús Fernández-Villaverde, Michael Johannes, Peter Karadi, Burçin Kısacıkoglu, Ulrich Müller, Giorgio Primiceri and numerous seminar and conference participants for useful comments.

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post the estimated shocks can be naturally labeled as the current fed funds rate 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](#)).

To estimate the structural shocks I exploit a striking, yet hitherto neglected feature of the data. Namely, the high-frequency reactions of financial variables, such as interest rates and stock prices, to FOMC announcements are usually very small, but sometimes very large, i.e. they have very fat tails, or excess kurtosis. This feature implies that these data may contain information about the nature of the underlying structural shocks. Given the importance of the Fed policies, it is vital to exploit this available information as well as possible. Previous literature on high-frequency reactions of financial variables to central bank announcements has ignored it, treating the shocks explicitly or implicitly as Gaussian. This paper is, to my knowledge, the first attempt to tap this valuable source of information.

Intuitively, fat-tailed shocks can be identified from the data because they tend to produce informative case studies. When we see a significant market reaction to an FOMC announcement, and the underlying shocks are independent and fat-tailed, there is a high chance that only a subset of the shocks is driving this reaction, while the others are very small. This greatly facilitates detecting the unique patterns in the data corresponding to individual shocks. As a result, the shocks are identifiable from the data via the likelihood function alone, even in the absence of economic identifying restrictions. One contribution of this paper is to provide the intuition of the identification based on fat tails using a simple supply and demand example. The example also illustrates how identification weakens, and possibly vanishes, when the independence assumption is relaxed, which is potentially relevant in the case of disentangling Fed policies.

It is a separate question why the Fed shocks’ reflections in financial data are fat tailed. One reason could be that the Fed generally avoids surprising financial markets, until occasionally it is forced to do it big time. Another reason could be that investors process information imperfectly and focus only on the most salient dimensions ([Van Nieuwerburgh and Veldkamp, 2010](#)).

My 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 near-term fed funds futures, with a diminishing effect on longer maturities, and depresses the stock prices. It can be naturally labeled as the standard monetary policy shock. 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 has a similar impact on the yield curve as 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. \(2012\)](#). I find very similar four shocks when repeating the estimation on the principal components of a larger dataset and under a variety of other

modifications of the baseline model.

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. The shocks gradually propagate through the financial system and after a few days get reflected in the corporate bond spreads and breakeven inflation rates. Also the Delphic forward guidance shocks have significant and persistent effects on financial variables and contribute to the historical narrative of Fed policies. One of the largest Delphic shocks occurs in August 2011, when the Fed stated that exceptionally low interest rates will be warranted at least through mid-2013, triggering pessimism about the economy.

It is important that the results are robust to relaxing the assumption that the structural shocks are independent. If different Fed shocks tend to be large simultaneously (e.g. if they have some common stochastic volatility), the identification from fat-tails gets diluted and eventually vanishes (e.g. Montiel Olea et al., 2022). However, even accounting for this possibility, I still find enough independent variation to yield tight identification and virtually the same estimated shocks.

Previous research has used a variety of approaches and assumptions to decompose the high-frequency financial market reactions into economically interpretable components (see Gürkaynak et al., 2005; Cieślak and Schrimpf, 2019; Jarociński and Karadi, 2020; Swanson, 2021; Inoue and Rossi, 2021; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023; Lewis, 2023, and others). Most of these papers ignore the non-Gaussianity in the data and construct the shocks with the a priori assumed features. They often use identifying restrictions familiar from the Structural VAR literature. For example, Gürkaynak et al. (2005) separate the target factor (standard monetary policy) from the path factor (forward guidance) imposing a *zero restriction* on the response of short term rates to forward guidance. Swanson (2021) imposes a *narrative restriction* that the asset purchase shock is small prior to the Zero Lower Bound (ZLB) period. Jarociński and Karadi (2020) separate monetary policy (a summary of standard and non-standard policies) from information (Delphic) shocks using *sign restrictions*. It is very interesting that, although I do not impose any of these restrictions, the shocks I estimate satisfy them (sometimes up to a numerical approximation). They are also highly correlated with their counterparts in these papers. Thus, my approach provides a statistical validation of the assumptions imposed in these papers. That said, I refine these papers' interpretations of the data by distinguishing four main shocks, while they identify at most three.

Identification through non-Gaussianity, such as the excess kurtosis exploited here, has been known since the 1990s but economic applications have started to appear only recently. 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 (SVARs) with Student-t shocks. Gouriéroux et al. (2017) extend the inference on SVARs 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. Fiorentini and Sentana (2020) study the effects of distributional misspecification and identify an SVAR of volatility indices. Drautzburg and Wright (2021) use non-Gaussianity to strengthen the identification in sign-restricted in VARs. Braun (2023)

applies identification through non-Gaussianity to the oil market, [Anttonen et al. \(2023\)](#) use it to study fiscal multipliers. [Davis and Ng \(2022\)](#) provide econometric theory for VARs with disaster-type shocks and apply it to economic uncertainty and Covid shocks.

Several recent papers exploit the non-Gaussianity of financial variables for the identification of macroeconomic SVARs that include a monetary policy shock. [Maxand \(2020\)](#) estimates an SVAR for the US that includes the fed funds rate and stock prices, and finds a non-Gaussian monetary policy shock. [Lanne and Luoto \(2020\)](#) and [Anttonen et al. \(2021\)](#) study the effects of the US monetary policy shock in the SVAR of [Uhlig \(2005\)](#) generalized to allow for non-Gaussian shocks and find that the monetary policy shock has very fat tails. [Lanne and Luoto \(2021\)](#) estimate an illustrative 3-variable non-Gaussian SVAR including the fed funds rate, with a highly non-Gaussian monetary policy shock. [Andrade et al. \(2023\)](#) document that many proxies of monetary policy shocks studied in the earlier literature exhibit fat tails and use this feature to sharpen the identification in their non-Gaussian SVARs. These papers work with financial variables at the monthly frequency and identify a single monetary policy shock. The present paper is different in that it works with the high-frequency reactions of financial variables to FOMC announcements and uses non-Gaussianity to distinguish between different types of Fed policies.

There are analogies between identification by non-Gaussianity and identification by heteroskedasticity ([Rigobon, 2003](#)). Both approaches are examples of a statistical identification exploiting that the shocks arrive “irregularly”. For some recent applications of identification by heteroskedasticity see e.g. [Lewis \(2023, 2022, 2021\)](#); [Brunnermeier et al. \(2021\)](#); [Miescu \(2021\)](#). In particular, [Lewis \(2023\)](#) also identifies the effects of the Fed policies from high-frequency financial data, and, remarkably, finds similar four dimensions of monetary policy. This is notable, because his approach is very different from the present paper. Lewis exploits the intraday time variation of the asset price volatility on the days of FOMC announcements. On each of these days he fits a separate time series model and performs a separate identification. By contrast, here each FOMC announcement contributes only one observation and I rely on contrasting financial market reactions across the announcements.

The rest of the paper is structured as follows. Section 2 presents the data, highlighting their excess kurtosis. Section 3 lays out the baseline econometric model and explains the identification with a simple example. Section 4 reports the estimation results for the baseline model. Section 5 summarizes the lessons from alternative estimations reported in detail in the Online Appendix. Section 6 tracks the longer term effects of the shocks using daily local projections. Section 7 concludes.

2 Data

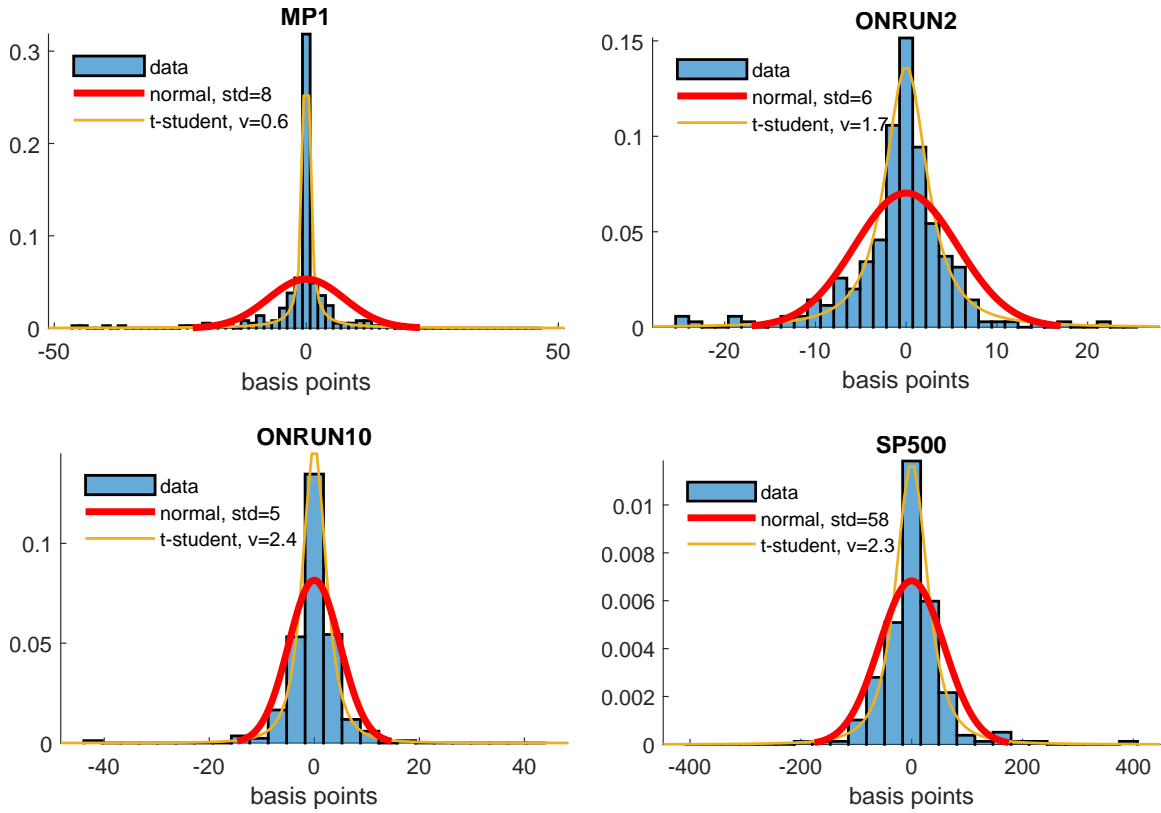
The data on high-frequency financial market reactions to FOMC announcements come from the widely-used dataset of [Gürkaynak et al. \(2005\)](#) (GSS from now on) updated by [Gürkaynak et al. \(2022\)](#). This dataset contains the changes of financial variables in a 30-minute window around FOMC announcements (from 10 minutes before to 20 minutes after the announcement). The sample studied here contains 241 FOMC announcements from 5 July 1991 to 19 June 2019.

In the baseline analysis I consider a vector of four variables (later I also extract factors

from a larger set of variables). I refer to the variables 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 FOMC announcement. 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 \(2021\)](#), who finds that these three variables approximately span the target, path and LSAP factors that he constructs. 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 the Gaussian densities, plotted in red, fit the histograms poorly. First, the Gaussian distributions 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 ($v = 0.6, 1.7, 2.4, 2.3$, respectively) implying very large departures from Gaussianity.

If we think of these variables as being linear combinations of Fed policy shocks, their non-Gaussianity implies that at least one, and possibly more of these shocks are non-Gaussian.

3 The econometric model and identification

Throughout this paper I assume that market responses to FOMC announcements are generated by the following simple model driven by potentially fat-tailed shocks:

$$y_t = C' u_t, \quad u_t \sim \text{i.i.d.} p(u_t). \quad (1)$$

$y_t = (y_{1,t}, \dots, y_{N,t})'$ is a vector of N variables observed at time t . $u_t = (u_{1,t}, \dots, u_{N,t})'$ is a vector of unobserved, structural (i.e. uncorrelated) shocks coming from a density $p(u_t)$ which may exhibit fat tails. C is an $N \times N$ matrix whose i, j -th element $C(i, j)$ contains the effect of shock i on variable j .¹

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 fat tails (excess kurtosis) and a sufficient degree of independence. For formal proofs that non-Gaussianity (of a more general form) of all but one shocks implies identification see e.g. [Lanne et al. \(2017\)](#), Proposition 2, or the discussion in [Sims \(2021\)](#).²

For a simple illustration, consider a market for good A. Market prices P and quantities Q are determined by demand and supply, each subject to shocks. ΔP and ΔQ are the innovations in P and Q in response to shocks. 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 flat and the supply schedule is steep, while in Model 2 it is the reverse. Models 1 and 2 satisfy equation (1) with coefficients C_1 and C_2 respectively,

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

where u^s is a supply shock and u^d a demand shock. In Model 1 a unit supply shock u^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 u^s and u^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

¹Equation (1) is a special case of a Structural VAR with no lags of y_t . The lack of any lags in equation (1) is consistent with the standard assumption in the high-frequency monetary policy surprise literature that those surprises should not be predictable with any information that predates the surprise.

²Departures from Gaussianity other than fat tails also yield identification and do not necessarily require independence. See [Bonhomme and Robin \(2009\)](#); [Anttonen et al. \(2023\)](#) for conditions under which skewed shocks are identifiable and [Mesters and Zwiernik \(2022\)](#) for other minimal conditions for identifiability.

obtained from Model 1 in panel C and from Model 2 in panel D, when the shocks u^s and u^d are drawn from independent Gaussian distributions with mean 0 and variance 1. In this example $C_1 \times C_1' = C_2 \times C_2' = \begin{pmatrix} 1 & 0.2 \\ 0.2 & 1 \end{pmatrix}$. Consequently, in both cases $(\Delta P, \Delta Q)$ are Gaussian with the same first two moments, $(0, 0)$ and $\begin{pmatrix} 1 & 0.2 \\ 0.2 & 1 \end{pmatrix}$, so the samples look the same.

However, when shocks u^s and u^d are independent Student-t, the situation changes. Now Models 1 and 2 produce systematically different combinations of ΔP and ΔQ . This is

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

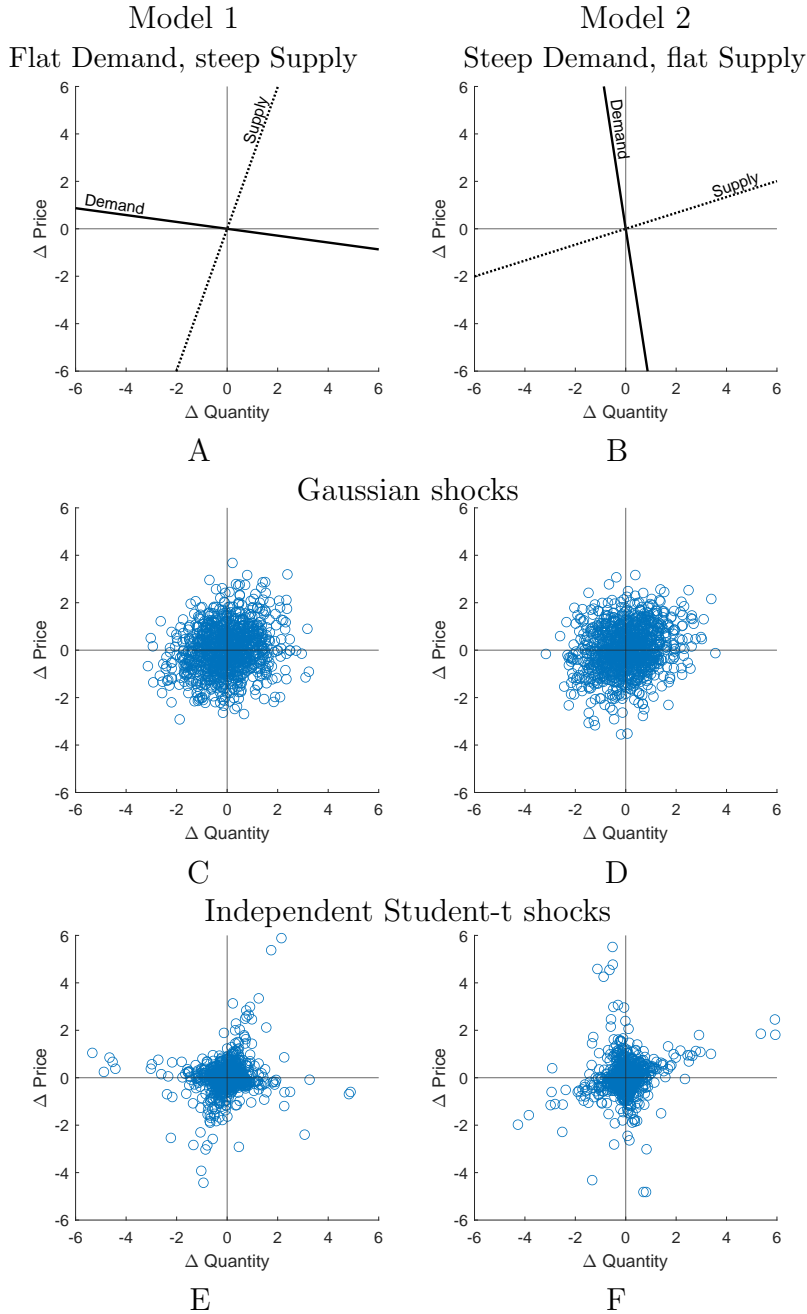
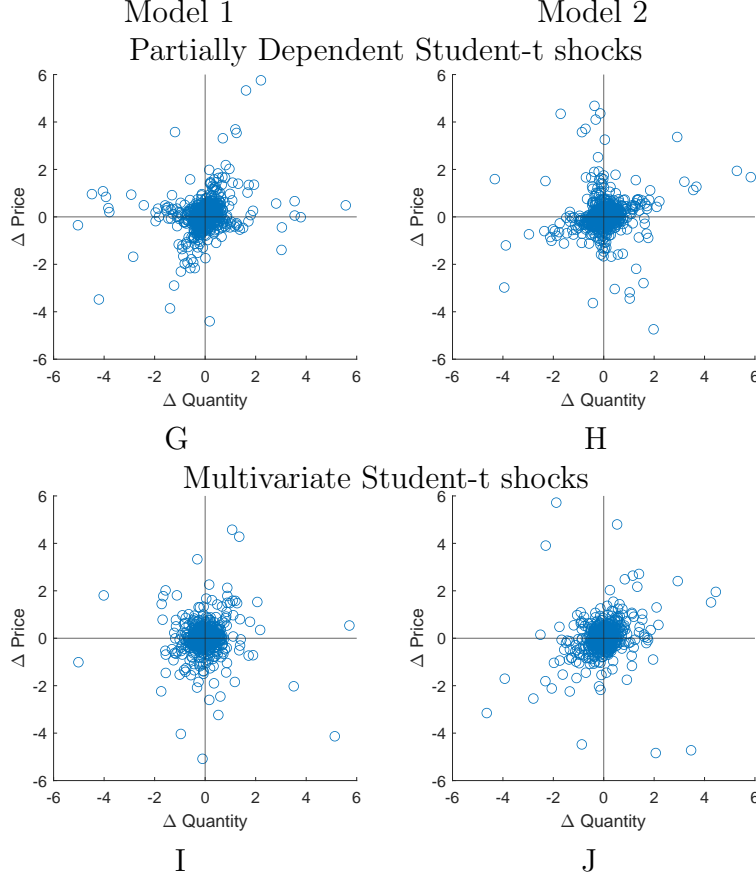


Figure 2: Continued



Note. Each scatter plot has 1000 observations. The samples in the left column are generated from (2) with coefficients C_1 , and the samples in the right column are generated with coefficients C_2 . In panels C and D the shocks u^d and u^s are independent Gaussian with mean 0 and variance 1. In panels E and F the shocks u^d and u^s are independent Student-t with mean 0, scale parameter 1 and shape parameter $\nu = 1.5$. In panels G and H the shocks u^d and u^s are drawn from the Partially Dependent Multivariate t distribution defined in Online Appendix G, with mean 0 and parameters $\nu_0 = 0.85$ and $\bar{\nu} = 0.65$. In panels I and J the shocks are drawn from the Multivariate Student-t with mean 0, scale parameter identity matrix and shape parameter $\nu = 1.5$. Before feeding to the model, the shocks are re-scaled so that their sample standard deviations equal 1. In all scatter plots, ΔP and ΔQ have sample mean zero, sample variance 1 and sample correlation 0.2.

illustrated in the third row of Figure 2. The samples in the third row are generated from (2) but this time shocks u^s and u^d are drawn from independent Student-t distributions with mean 0 and shape parameter $\nu = 1.5$. For comparability with the previous example, the drawn shocks are re-scaled to ensure that their sample variance is 1. Hence, $(\Delta P, \Delta Q)$ continue to have the same first two sample moments, $(0, 0)$ and $(\frac{1}{0.2} \ 0.2)$. 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. Obviously, if we can identify the structural model visually, we can also do it numerically by evaluating the likelihood function (Online Appendix A presents an example).

Independence of the shocks helps but is not necessary for identification. In panels G and H the shocks are no longer independent. In particular, they continue to be marginally Student-t and orthogonal, but when one of them is large in absolute value, the other one is also more likely to be large in absolute value. This blurs the picture compared with the case of independence, because there are more cases when both shocks are large, producing outliers that lay far away from either of the curves. Nevertheless, we can still distinguish the models. Only in the limiting case of extreme dependence, shown in panels I and J, identification vanishes (the shocks here come from a 2-dimensional Multivariate Student-t distribution). In the presence of less extreme dependence the models continue to be identifiable.

3.2 Estimation

In the rest of the paper model (1) is taken to the data. For a sample of T observations the model can be written as

$$Y = UC, \quad (3)$$

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 $YW = U$.

3.2.1 The baseline model

The baseline model assumes that the shocks in period t are independent Student-t, i.e. $p(u_t) = \prod_{n=1}^N p(u_{n,t})$ and shock $u_{n,t}$ comes from a Student-t density with v_n degrees of freedom, denoted $\mathcal{T}(v_n)$, with the probability density function

$$p(u_{n,t}) = c(v_n) (1 + u_{n,t}^2/v_n)^{-\frac{v_n+1}{2}}, \quad (4)$$

where $c(v_n) = v_n^{-1/2} B(\frac{1}{2}, \frac{v_n}{2})^{-1}$ is the integrating constant and $B(\cdot, \cdot)$ is the beta function. As $v_n \rightarrow \infty$ the Student-t distribution converges to the Gaussian distribution, so this model accommodates the case where some or all shocks are Gaussian. Let v denote the length- N vector $v = (v_1, \dots, v_N)$.

The log-likelihood of sample Y is

$$\log p(Y|W, v) = T \log |\det W| - \sum_{t=1}^T \sum_{n=1}^N \frac{v_n + 1}{2} \log(1 + u_{n,t}^2/v_n) + T \sum_{n=1}^N \log c(v_n), \quad (5)$$

where $u_{n,t} = y'_t w^n$, with w^n the n -th column of W .

I start by maximizing the likelihood (5) to obtain point estimates \hat{W} and $\hat{v} = (\hat{v}_1, \dots, \hat{v}_N)$, the structural shocks $\hat{U} = Y\hat{W}$ and the impact matrix $\hat{C} = \hat{W}^{-1}$. Online Appendix B

provides the analytical expression for the gradient of the likelihood which improves the speed and precision of the maximization.

To cross-check these results and to assess the estimation uncertainty I estimate the model with the Bayesian approach using a noninformative prior for W (the prior for v needs to be proper for technical reasons, see [Bauwens and Lubrano 1998](#), but I use a conservative prior that mildly works *against* identification). I use Bayesian simulation (Metropolis-Hastings algorithm) to study the shape of the likelihood function more systematically and to make the inference about nonlinear functions of W , such as C , as precise as possible, instead of relying on asymptotic approximations. Online Appendix B provides the details on the Bayesian estimation.

3.2.2 Relaxing independence: the PDMT model

In a robustness check I relax the independence assumption and assume that the shocks come from the new Partially Dependent Multivariate t-distribution (PDMT) defined in Online Appendix G. In this joint distribution each shock u_{tn} is marginally Student-t and uncorrelated with the other shocks, but they are not independent because their large absolute values tend to occur at the same time. The extent to which this happens is governed by the estimated parameters of the distribution.

3.3 The problem of shock permutation

One peculiarity of model (1) is that it is only identified up to permutation and signs of the shocks: permuting the shocks ($N!$ possibilities) and flipping their signs (2^N possibilities) does not change the value of the likelihood function. Therefore, if the maximization of the likelihood detects a local mode \hat{W}, \hat{v} , we know that there are also $N! \times 2^N - 1$ other local modes with the same value of the likelihood function. A Bayesian posterior simulator may visit the neighborhoods of different modes, and for a given draw of W one cannot be sure to what signs and ordering of the shocks it corresponds.

This paper proposes a practical approach for normalizing the draws, i.e. mapping them into the same signs and ordering of the shocks. It takes one local mode \hat{W} as the reference point. Then, for each draw it finds shock signs and ordering that has *the highest probability under the Gaussian approximation of the likelihood function around \hat{W}* . Online Appendix C provides the details and an illustration.

In the literature the dominant solution of the permutation and sign switching problem is to use a non-exchangeable prior on the columns of W (e.g. [Brunnermeier et al., 2021](#)). The advantage of this paper's approach is that it does not require an informative prior on W . Its disadvantage is that it relies on the local Gaussian approximation of the shape of the likelihood and might not perform well when this approximation is poor.

4 Estimation results for the baseline model

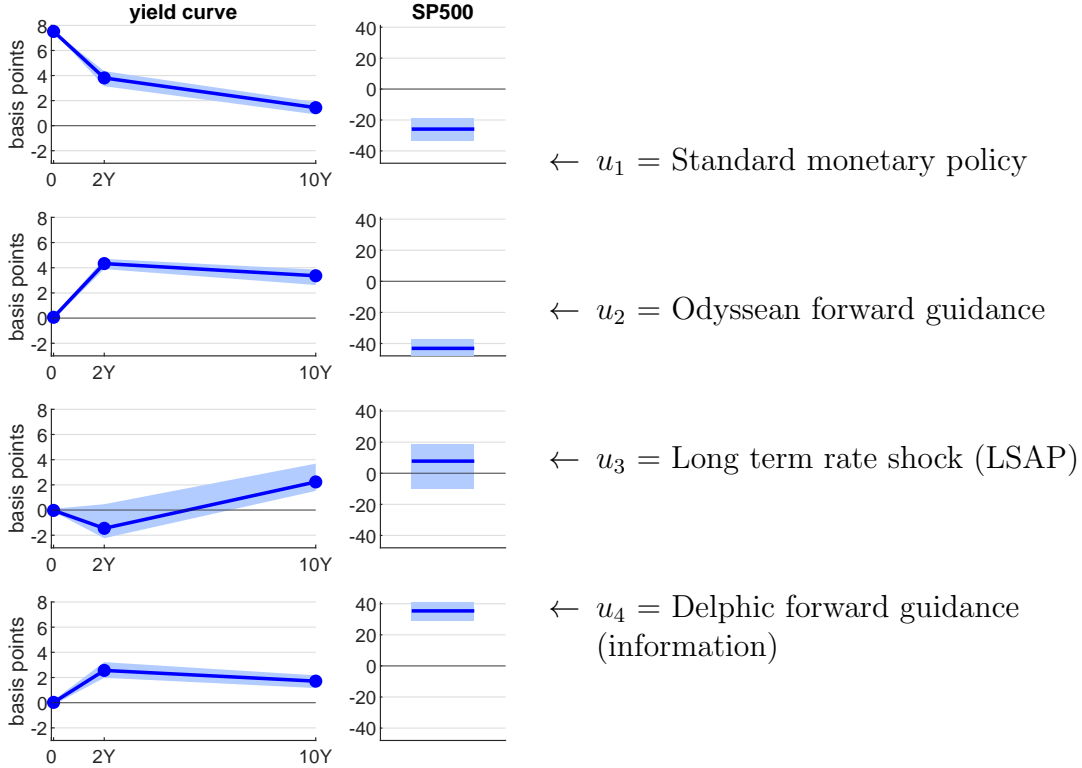
I define $y_t = (\text{MP1}, \text{ONRUN2}, \text{ONRUN10}, \text{SP500})$ and estimate model (1) with independent Student-t shocks (4) by maximum likelihood, obtaining the point estimates $\hat{W}, \hat{v}, \hat{U} =$

$Y\hat{W}, \hat{C} = \hat{W}^{-1}$. Next, I simulate the Bayesian posterior under a flat prior for W and store 2000 approximately independent draws. Either approach suggests that the model is well identified, with four very fat-tailed shocks and modes of W corresponding to alternative signs and permutations well separated by regions of very low likelihood.

4.1 The impact effects of the four baseline shocks

Figure 3 reports the impacts of the shocks implied by the estimated \hat{C} , together with the 95% Bayesian posterior probability ranges. To facilitate interpretation and comparisons with the literature, Figure 3 reports the effects of one-sample-standard-deviation shocks. That is, each row in this figure represents a row of C scaled by the sample standard deviation of the corresponding column of \hat{U} .³ Furthermore, the responses of interest rates are arranged into a yield curve, with the maturities on the x-axis.

Figure 3: Responses of the variables to standardized shocks, 95% bands.



The shocks reported in Figure 3 are tightly estimated and have intuitive economic interpretations.

³Parameter C gives the responses of Y to the shocks U that have different scales determined by the properties of $\mathcal{T}(v_n)$. The population standard deviations of the shocks are $\sqrt{\frac{v_n}{v_n-2}}$ for $v_n > 2$ and infinite or undefined otherwise, but one can always compute the sample standard deviation of \hat{U} .

u_1 looks like a standard contractionary monetary policy shock. The fed funds rate 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 43 basis points.

u_3 mostly affects the 10-year yield, while having little effect on anything else, except the 2-year rate, which falls a little. However, I show later that in the second half of the sample this shock has a significant negative impact on the stock market and a positive impact on the 2-year rate. Furthermore, its large realizations coincide with important announcements of asset purchase policies, 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, which can be rationalized by the presence of the Fed information effect. In particular, this shock perfectly matches the notion of the Delphic forward guidance of [Campbell et al. \(2012\)](#).

The effects of u_1 and u_2 on MP1 and Treasury yields are very similar to the effects of the target factor and path factor of [GSS](#) and [Swanson \(2021\)](#) (see e.g. Swanson’s Table 3). This is in spite of the fact that I do not impose any of their identifying restrictions. Furthermore, 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 , and they manifest themselves as the Delphic forward guidance. The theoretical models of [Melosi \(2017\)](#) and [Nakamura and Steinsson \(2018\)](#) focus on the information effects that accompany *current* fed fund rate changes, but this paper’s agnostic estimation picks up the information effects in the forward guidance.

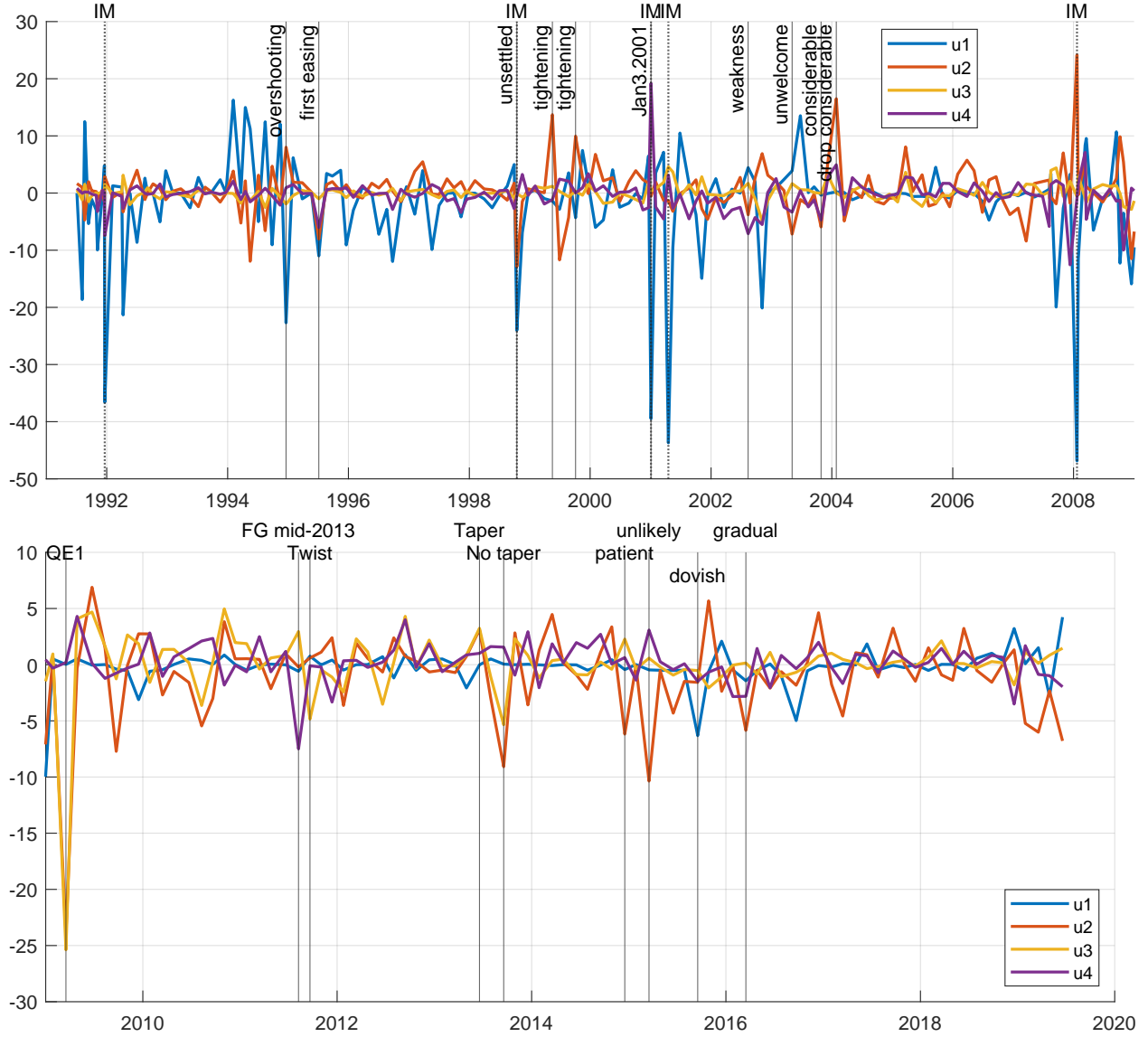
4.2 The estimated shocks: the history

Figure 4 reports the history of the shocks over time. To facilitate interpretation, in this figure the shocks are rescaled so that a unit u_1 shock raises the MP1 by 1 basis point, a unit u_2 and u_4 raises the ONRUN2 by 1 basis point, and a unit u_3 shock raises the ONRUN10 by 1 basis point.⁵ The top panel of Figure 4 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 \(2021\)](#). (For reference, Online Appendix J provides the responses of the variables y_t to each of these events.)

⁴[Swanson \(2021\)](#) also finds that his LSAP shock has an insignificant effect on the stock prices in the full sample.

⁵To achieve that, \hat{u}_1 is multiplied by its effect on MP1, given by $\hat{c}_{1,1}$, \hat{u}_2 and \hat{u}_4 are multiplied by their effects on ONRUN2, given by $\hat{c}_{2,2}$ and $\hat{c}_{4,2}$, respectively, and \hat{u}_3 is multiplied by its effect on ONRUN10, given by $\hat{c}_{3,3}$.

Figure 4: The estimated shocks over time.



Note. The shocks are re-scaled as explained in footnote 5. IM denotes an “inter-meeting” announcement.

The history of the standard monetary policy shock u_1 agrees with the accepted accounts. This is not surprising because u_1 is essentially equal to MP1 (the rank correlation of u_1 with MP1 is 0.99). It is also highly correlated with the [GSS target factor/Swanson \(2021\)](#) fed funds rate shock (rank correlation 0.76, linear correlation 0.95, see Table 1). 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). Unsurprisingly, in the Zero Lower Bound period 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 1 reports that the forward guidance shock of [Swanson \(2021\)](#) 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 4 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. This is a large inter-meeting rate cut that, as discussed in GSS, caused financial markets to mark down the probability of 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 extremely large, 400bp increase in the S&P500. Since this u_4 shock is so large and its market interpretation tricky to interpret,⁶ I test the robustness of the results to dropping the January 3, 2001 observation from the sample and re-estimating the model. The results without this observation are very similar. The rank correlation of the two estimates of u_4 on the remaining dates is 0.99 (Table 1).

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, while the announcement did not promise a rate cut explicitly, it worked as a Delphic forward guidance.

In the 2009-2019 plot in Figure 4 the largest Delphic shock is the ‘mid-2013’ announcement, issued on August 9, 2011, in which the FOMC stated that the “economic conditions ... are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013”. It is intuitive that such a wording of the forward guidance is prone to trigger a Delphic interpretation (e.g. Del Negro et al. 2023 discuss the Delphic nature of this announcement). 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 (2021), 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 small Odyssean and Delphic forward guidance shocks of -1.5 basis points each. However, there are few other so clear discrepancies between the two

⁶The Fed stated that “there is little evidence to suggest that longer-term advances in technology and associated gains in productivity are abating” and cited recent signals of economic weakness as the reason for the cut, but market commentary focused mainly on the latter.

approaches.

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 1). 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.

Table 1: 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
<i>Changing the sample</i>					
Drop January 3, 2001	240	u_1 : 1.00 (1.00)	u_2 : 0.92 (0.89)	u_3 : 0.95 (0.98)	u_4 : 0.99 (1.00)
Drop QE1 (March 18, 2009)	240	u_1 : 0.999 (1.000)	u_2 : 0.998 (0.999)	u_3 : 0.998 (0.998)	u_4 : 0.996 (0.999)
Sample 1991-2004	120	u_1 : 0.94 (0.99)	u_2 : 0.88 (0.95)	u_3 : 0.92 (0.94)	u_4 : 0.97 (0.99)
Sample 2005-2019	121	u_1 : 1.00 (1.00)	u_2 : 0.82 (0.77)	u_3 : 0.88 (0.97)	u_4 : 0.96 (0.98)
<i>Other papers</i>					
Swanson (2021)	241	ff: 0.79 (0.95)	fg: 0.75 (0.81)	lsap: -0.66 (-0.84)	fg: 0.47 (0.48)
JK (2020) FF4	221	MP: 0.43 (0.69)	MP: 0.63 (0.45)	MP: -0.05 (-0.04)	CBI: 0.59 (0.66)
JK (2020) 1stPC	241	MP: 0.39 (0.67)	MP: 0.71 (0.56)	MP: -0.08 (-0.02)	CBI: 0.77 (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.

Table 1 shows the correlations between u_1, u_2, u_3, u_4 and the related shocks identified with very different techniques by Swanson (2021) and Jarociński and Karadi (2020). The standard policy shock u_1 is highly correlated with Swanson’s Fed Funds rate shock, the two forward guidance shocks u_2 and u_4 are both highly correlated with Swanson’s single forward guidance shock (he does not distinguish between Delphic and Odyssean forward guidance) and the LSAP shock u_3 is highly correlated with Swanson’s LSAP shock (I scale this shock

with the opposite sign). Jarociński and Karadi (2020) have a single catch-all monetary policy shock which is highly correlated both with u_1 and with u_2 (but does not capture asset purchases u_3). The Delphic shock u_4 is highly correlated with the central bank information (CBI) shock of Jarociński and Karadi (2020), which also 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 rank correlation is 0.59. 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 rank correlation is even higher, 0.77.

4.3 Further estimation results

Inspecting matrix W (reported in Online Appendix D) we can see that u_1 is essentially equal to the MP1, while the other shocks are non-trivial linear combinations of all variables. As can be inferred already from Figure 4, all the shocks are very fat tailed. The maximum likelihood estimates of the degree-of-freedom parameters are $\hat{v}_1 = 0.6$ (0.07), $\hat{v}_2 = 2.14$ (0.4), $\hat{v}_3 = 2.13$ (0.4) and $\hat{v}_4 = 2.0$ (0.4) (standard deviations in parentheses). Online Appendix D reports their posterior densities, which peak around the maximum likelihood estimates. When $v \leq 2$ the Student-t density does not have a finite variance. The finding that the Fed shocks are well characterized by a density without a finite variance echoes a similar finding in Anttonen et al. (2023) obtained with different data and with a more general shock density. These authors ascribe their finding to the presence of unmodeled conditional heteroskedasticity and the same reasoning applies here. Especially the first shock has very low volatility during the Zero Lower Bound period and much higher volatility otherwise. Explicit modeling of conditional heteroskedasticity might tighten the identification further but this is left for future research.

Online Appendix D reports also additional estimation results. The marginal posterior densities of the elements of W and C are very tight and approximately Gaussian. The posterior modes corresponding to different shock permutations are separated by very low probability regions and the posterior simulator never jumped between the permutations. The shocks do not have significant rank correlations. Large shocks tend to occur together (as can be seen also in Figure 4), suggesting that it may be useful to relax the independence assumption, but, as shown in the appendix, this has very little effect on the results.

5 Other exercises

This section summarizes other empirical results reported in detail in the Online Appendix.

First, the results are not sensitive to mis-estimation or mistaken restrictions on v , as long as it does not exceed the value of about 12. Online Appendix E studies this sensitivity. Instead of estimating v , it imposes values on the grid from 0.5 to 30, and estimates only C . It shows that the results are very similar for values $v < 12$.

When the model is estimated on subsamples, the LSAP shock u_3 is only detectable in the later part of the sample, which is intuitive because the LSAP policies were only introduced in the wake of the Great Financial Crisis. The remaining shocks are present throughout

the sample and have reasonably similar effects. The shocks estimated in subsamples are quite highly correlated with the respective shocks estimated on the full sample (see Table 1). Detailed sub-sample results are provided in Online Appendix F.

The variant of the model that assumes the PDMT distribution of the shocks does detect some dependence between the shocks. However, the shocks still exhibit enough independent variation to yield basically the same C , with only marginally larger posterior uncertainty. To push the model further I force the degree of dependence to be even higher by imposing a priori restrictions. These restrictions widen the uncertainty bands more visibly, but the key features of the shocks are still distinguishable. Moreover, when I evaluate these restrictions formally using Bayes factors they are very strongly rejected. More details of these exercises are provided in Online Appendix G. The key lesson from this analysis is that the shocks need not be fully independent to achieve meaningful identification. In the present empirical application the baseline results are robust to relaxing the assumption of independence.

Very similar four shocks are obtained when instead of the four variables included in the baseline model, the model is estimated on the first four principal components extracted from a larger set of GSS variables that includes more interest rates at various maturities. Online Appendix H reports the details. It also explores models with three or five shocks and with other information sets. Models with three shocks that include the SP500 surprise detect shocks very similar to u_1, u_2, u_4 . Models with three shocks that only include interest rates recover u_1, u_3 and a composite forward guidance shock (an amalgam of u_2 and u_4). The resulting three shocks closely resemble the shocks that Swanson (2021) estimates from the same information set but with very different methods. This result serves as another statistical validation of his exercise. Models with more than four shocks feature similar baseline four shocks and either yield additional Delphic shocks or a new shock that mainly affects the exchange rate.

6 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:

$$x_{t+h} - x_{t-1} = \alpha + \beta_h^i u_{i,t} + e_t, \quad (6)$$

where x_t is a daily financial variable and t is an FOMC announcement day. I consider horizons $h = 1, 3, 5, 10, 15, 20, 25$ business days. $u_{i,t}, i = 1, 2, 3, 4$ are one sample standard deviation shocks from the baseline model. The shocks are included in the regressions one-by-one. The quantity of interest is β_h^i , the effect of a one sample standard deviation shock. Equation (6) is estimated with OLS and with heteroskedasticity-robust errors, and a bootstrap procedure accounts for the uncertainty in the estimation of the shocks.⁷

⁷For each draw W^m , $m = 1, \dots, 2000$ from the posterior i) compute $U^m = YW^m$ and standardize it; ii) estimate regression (6) by OLS and store the point estimate of β_h^i and its Eicker-White (EHW) variance. The reported plots represent the means of the 2000 point estimates and the total variances computed from the 2000 EHW variances and point estimates using the law of total variance. Uncertainty about U increases these bands by on average 2.6% (and at most 14%) of the width of the bands conditional on the maximum likelihood estimates of the shocks.

Figure 5 reports local projection results where variable x is, respectively, the federal funds effective rate, 2-year and 10-year treasury yields, and the S&P500 stock price index (i.e. the daily analogues of the high-frequency variables entering the baseline model) as well as corporate bond spreads, breakeven inflation rates and exchange rate. Online Appendix I reports data sources and robustness to alternative variables.

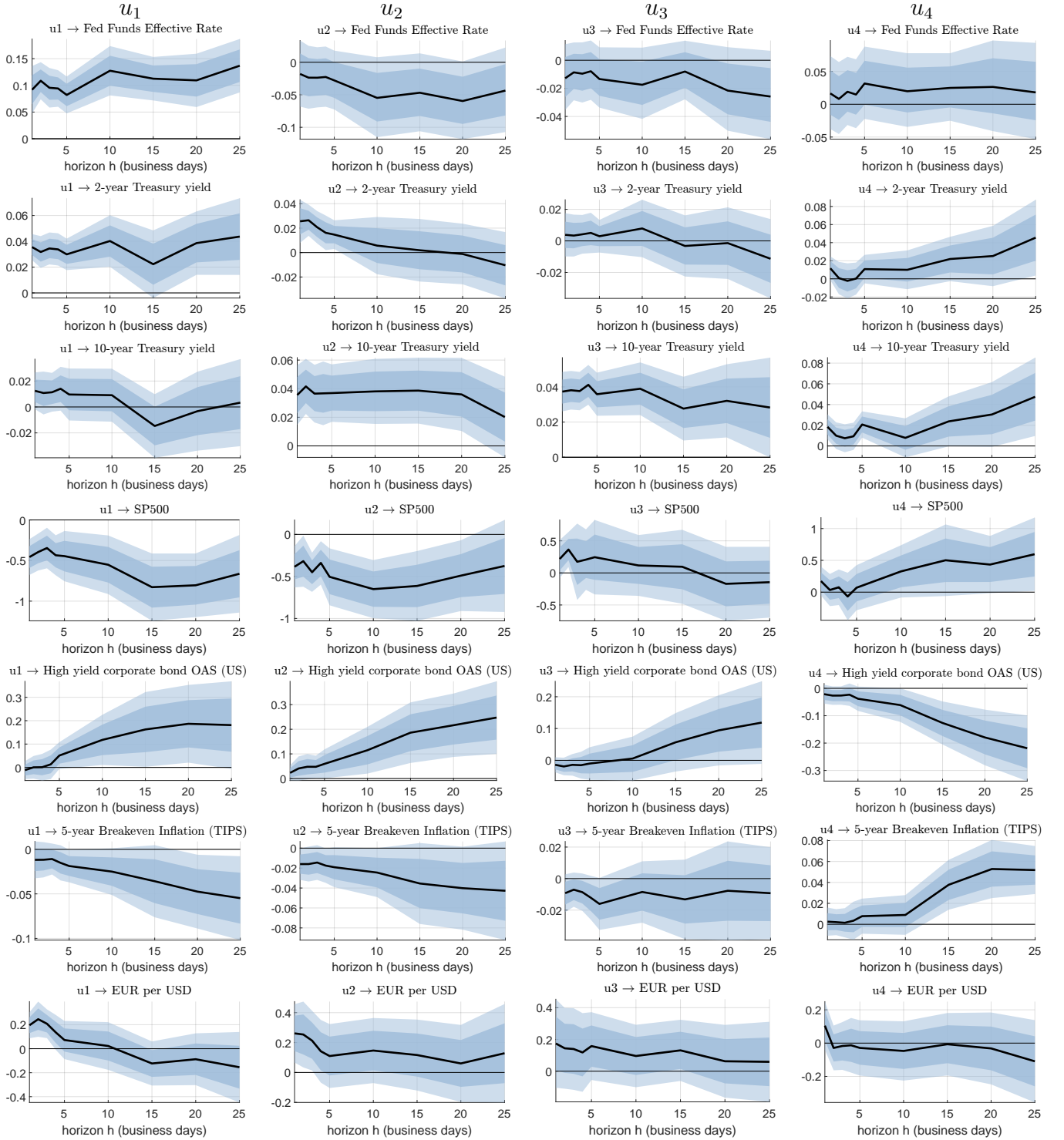
Four main lessons follow from these local projection results. First, the effects of the shocks on interest rates and stock prices in the first 30 minutes given by the matrix C are not just temporary blips. Most of them persist in the following days and weeks, some of them die out gradually and some, most notably for u_4 , get amplified over time. u_1 has a persistent effect on the short and medium (2-year) interest rates and the stock prices. u_2 has a persistent effect on the 10-year rate and stock prices, but its effect on the 2-year rate dies out within about 2 weeks, suggesting that it may be a weak instrument for the 2-year rate in lower frequency data. u_3 has a persistent effect on the 10-year rate and not on much else, echoing its high-frequency effects (the positive effect on stock prices is just a temporary blip). The Delphic shock u_4 triggers a dynamics that is different from all other shocks: its initial effects are not significant for the first four days, but gradually get amplified and both interest rates and stock prices are higher after one month than at the end of the FOMC day.

The second lesson from Figure 5 is that the shocks gradually propagate through the financial system and eventually have pronounced effects on the financial conditions in the economy. In particular, corporate bond spreads gradually increase after u_1, u_2, u_3 reflecting the tightening of monetary policy, and decline after u_4 , consistently with its Delphic character. By the end of the month the responses are large and statistically significant. Standard u_1 and u_2 shocks increase the high yield spread by about 20 bp, u_3 increases it by about 10 bp and u_4 reduces it by 20 bp. While Figure 5 plots the high yield bond spread, Online Appendix I shows that for other bond ratings the effects go in the same direction and that the spreads account for much of the responses of corporate bond yields, suggesting the importance of financial frictions in the transmission of monetary policy. It also reports similar responses of the broader National Financial Conditions Index.

The third lesson is that breakeven inflation rates gradually decline after contractionary monetary policy shocks u_1, u_2, u_3 and gradually increase after the Delphic shock u_4 . This might reflect intuitive reactions of inflation expectations to the shocks. These results could be also due to liquidity and/or inflation risk premia increasing after u_1, u_2, u_3 and declining after u_4 . Figure 5 presents the results for the 5-year breakeven rates. Online Appendix I reports on the term structure of breakeven rates, showing that the effects are more backloaded for u_1 and more frontloaded for u_2 and u_3 , with u_4 falling in-between.

The fourth lesson is that contractionary monetary policy shocks u_1, u_2, u_3 strengthen the dollar exchange rate, while the Delphic shock u_4 does not affect it much. Standard policy and forward guidance shocks u_1 and u_2 strengthen the dollar vs the euro statistically significantly by 20-25 bp. The effect of the asset purchase shock u_3 is quantitatively similar but estimated with a large uncertainty. The effect of the Delphic shock u_4 on the dollar is 10 bp on impact but is completely reversed after one day. This shock's little impact on the exchange rate is consistent with the role of the dollar as a 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, working against the standard uncovered interest rate parity effect of higher US interest rates. Online Appendix I shows that the findings on

Figure 5: The effects of the shocks on daily financial variables, local projection estimates



Note. The figure reports the effect of a 1-sample standard deviation shock based on local projections (6). The left-hand-side variables are in percent. Black line: OLS estimate conditional on the maximum likelihood estimate of the shocks. Darker blue: 1 standard deviation bands (68% probability). Lighter blue: 1.645 standard deviation bands (90% probability). The standard deviations are heteroskedasticity robust and account for the uncertainty in the estimation of the shocks, as explained in footnote 7.

the euro exchange rate mostly extend to other currencies, especially those of the advanced economies.

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 paper explains the intuition behind the fat tails-based identification and shows that it requires only a sufficient degree of independence, rather than full independence. It tracks the delayed effects of the estimated shocks on financial markets and finds that they eventually have pronounced effects on breakeven inflation rates and financial conditions, especially on the corporate bond spreads.

References

- Andrade, Philippe, Filippo Ferroni, and Leonardo Melosi (2023) “Identification Using Higher Order Moments Restrictions,” Working Paper Series WP 2023-28, Federal Reserve Bank of Chicago, [10.21033/wp-2023-28](https://doi.org/10.21033/wp-2023-28).
- Anttonen, Jetro, Markku Lanne, and Jani Luoto (2021) “Statistically Identified SVAR Model With Potentially Skewed and Fat-Tailed Errors,” Technical report, University of Helsinki, [10.2139/ssrn.3925575](https://doi.org/10.2139/ssrn.3925575), (Posted 20 September 2021; last revised 8 March 2023) Available at SSRN: <http://ssrn.com/abstract=3925575>.
- (2023) “Bayesian Inference on Fully and Partially Identified Structural Vector Autoregressions,” Technical report, University of Helsinki, [10.2139/ssrn.4358059](https://doi.org/10.2139/ssrn.4358059), (February 14, 2023) Available at SSRN: <http://ssrn.com/abstract=4358059>.
- 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](https://doi.org/10.1257/aeri.20180322).
- Bauer, Michael D. and Eric T. Swanson (2023) “A Reassessment of Monetary Policy Surprises and High-Frequency Identification,” *NBER Macroeconomics Annual*, 37 (1), 87–155, [10.1086/723574](https://doi.org/10.1086/723574).
- Bauwens, Luc and Michel Lubrano (1998) “Bayesian Inference on GARCH Models Using the Gibbs Sampler,” *The Econometrics Journal*, 1 (1), 23–46, [10.1111/1368-423X.11003](https://doi.org/10.1111/1368-423X.11003).
- 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](https://doi.org/10.1016/j.jeconom.2008.12.019).
- Braun, Robin (2023) “The importance of supply and demand for oil prices: Evidence from non-Gaussianity,” *Quantitative Economics*, 14 (4), 1163–1198, [10.3982/QE2091](https://doi.org/10.3982/QE2091).

- Brunnermeier, Markus, Darius Palia, Karthik A. Sastry, and Christopher A. Sims (2021) “Feedbacks: Financial Markets and Economic Activity,” *American Economic Review*, 111 (6), 1845–1879, [10.1257/aer.20180733](https://doi.org/10.1257/aer.20180733).
- 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](https://doi.org/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](https://doi.org/10.1016/0165-1684(94)90029-9).
- Davis, Richard and Serena Ng (2022) “Time Series Estimation of the Dynamic Effects of Disaster-Type Shock,” Technical Report arXiv:2107.06663v2, ArXiv, [10.48550/arXiv.2107.06663](https://arxiv.org/abs/2107.06663).
- Del Negro, Marco, Marc P. Giannoni, and Christina Patterson (2023) “The Forward Guidance Puzzle,” *Journal of Political Economy Macroeconomics*, 1 (1), 43–79, [10.1086/724214](https://doi.org/10.1086/724214).
- Drautzburg, Thorsten and Jonathan H. Wright (2021) “Refining Set-Identification in VARs through Independence,” NBER Working Papers 29316, National Bureau of Economic Research, Inc, [10.3386/w29316](https://doi.org/10.3386/w29316).
- Fiorentini, Gabriele and Enrique Sentana (2020) “Discrete Mixtures of Normals Pseudo Maximum Likelihood Estimators of Structural Vector Autoregressions,” Working Papers wp2020-2023, CEMFI, https://ideas.repec.org/p/cmfi/wpaper/wp2020_2023.html.
- 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, [10.1016/j.jeconom.2016.09.007](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](https://doi.org/10.1093/restud/rdz028).
- Gürkaynak, Refet S., Hatice Gökçe Karasoy-Can, and Sang Seok Lee (2022) “Stock Market’s Assessment of Monetary Policy Transmission: The Cash Flow Effect,” *Journal of Finance*, 77 (4), 2375–2421, [10.1111/jofi.13163](https://doi.org/10.1111/jofi.13163).
- 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 (2021) “A new approach to measuring economic policy shocks, with an application to conventional and unconventional monetary policy,” *Quantitative Economics*, 12 (4), 1085–1138, [10.3982/QE1225](#).
- 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](#).
- 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 and Jani Luoto (2020) “Identification of Economic Shocks by Inequality Constraints in Bayesian Structural Vector Autoregression,” *Oxford Bulletin of Economics and Statistics*, 82 (2), 425–452, [10.1111/obes.12338](#).
- (2021) “GMM Estimation of Non-Gaussian Structural Vector Autoregression,” *Journal of Business & Economic Statistics*, 39 (1), 69–81, [10.1080/07350015.2019.1629940](#).
- 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 (2021) “Identifying Shocks via Time-Varying Volatility,” *The Review of Economic Studies*, 88 (6), 3086–3124, [10.1093/restud/rdab009](#).
- Lewis, Daniel J. (2022) “Robust Inference in Models Identified via Heteroskedasticity,” *The Review of Economics and Statistics*, 104 (3), 510–524, [10.1162/rest_a_00963](#).
- (2023) “Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Effects,” *The Review of Economics and Statistics*, 1–46, [10.1162/rest_a_01315](#).
- Maxand, Simone (2020) “Identification of independent structural shocks in the presence of multiple Gaussian components,” *Econometrics and Statistics*, 16, 55–68, [10.1016/j.ecosta.2018.10.005](#).
- Melosi, Leonardo (2017) “Signalling Effects of Monetary Policy,” *The Review of Economic Studies*, 84 (2), 853–884, [10.1093/restud/rdw050](#).
- Mesters, Geert and Piotr Zwiernik (2022) “Non-Independent Component Analysis,” Technical report, Universitat Pompeu Fabra, <https://www.geertmesters.com/>.
- Miescu, Mirela (2021) “Forward guidance and conventional monetary policy shocks: identification and assessment,” mimeo, Lancaster University.
- Miranda-Agrippino, Silvia and Giovanni Ricco (2021) “The Transmission of Monetary Policy Shocks,” *American Economic Journal: Macroeconomics*, 13 (3), 74–107, [10.1257/mac.20180124](#).

- Montiel Olea, José Luis, Mikkel Plagborg-Møller, and Eric Qian (2022) “SVAR Identification From Higher Moments: Has the Simultaneous Causality Problem Been Solved?” *AEA Papers and Proceedings*, 112, 481–85, [10.1257/pandp.20221047](https://doi.org/10.1257/pandp.20221047).
- 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](https://doi.org/10.1093/qje/qjy004).
- Rigobon, Roberto (2003) “Identification Through Heteroskedasticity,” *The Review of Economics and Statistics*, 85 (4), 777–792, [10.1162/003465303772815727](https://doi.org/10.1162/003465303772815727).
- Sims, Christopher A. (2021) “SVAR Identification through Heteroskedasticity with Misspecified Regimes,” Technical report, Princeton University, <http://sims.princeton.edu/yftp/bpss/IDHmsspcfdRgms.pdf>.
- Swanson, Eric T. (2021) “Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets,” *Journal of Monetary Economics*, 118, 32–53, [10.1016/j.jmoneco.2020.09.003](https://doi.org/10.1016/j.jmoneco.2020.09.003).
- Uhlig, H. (2005) “What are the effects of monetary policy on output? Results from an agnostic identification procedure,” *Journal of Monetary Economics*, 52 (2), 381–419, [10.1016/j.jmoneco.2004.05.007](https://doi.org/10.1016/j.jmoneco.2004.05.007).
- Van Nieuwerburgh, Stijn and Laura Veldkamp (2010) “Information Acquisition and Under-Diversification,” *Review of Economic Studies*, 77 (2), 779–805, [10.1111/j.1467-937X.2009.00583.x](https://doi.org/10.1111/j.1467-937X.2009.00583.x).