STAFF REPORTS

NO. 891
JUNE 2019

REVISED
JULY 2022

Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Macroeconomic Effects

Daniel J. Lewis

FEDERAL RESERVE BANK *of* NEW YORK

Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Macroeconomic Effects

Daniel J. Lewis

Federal Reserve Bank of New York Staff Reports, no. 891
June 2019; revised July 2022
JEL classification: E44, E52, E58, C32, C58

Abstract

I propose to identify announcement-specific decompositions of asset price changes into monetary policy shocks exploiting heteroskedasticity in intraday data, accommodating both changes in the nature of shocks and the state of the economy across announcements. I compute decompositions with respect to fed funds, forward guidance, asset purchase, and Fed information shocks from 1996 to 2019. The decompositions illustrate which announcements of unconventional policy measures had significant effects during the Great Recession. Forward guidance and asset purchases have significant effects on yields, spreads, equities, and uncertainty. Positive shocks to all dimensions of monetary policy trigger macroeconomic contractions, while information shocks telegraph expansions.

Key words: high-frequency identification, time-varying volatility, monetary policy shocks, forward guidance, quantitative easing

---

Lewis: Federal Reserve Bank of New York (email: daniel.lewis@ny.frb.org). The author thanks Richard Crump, Raffaella Giacomini, Domenico Giannone, Simon Gilchrist, David Lucca, and Mikkel Plagborg-Möller for feedback, Taeyoung Doh and Eric Swanson as discussants, three anonymous referees, Olivier Coibion as editor, seminar participants at the NBER Summer Institute 2019, Philadelphia Fed, Université de Montreal, University of Pennsylvania, the ECB, Oxford, UCL, and UBC Sauder, conference participants, and Mary Quiroga, Eric Qian, Christopher Simard, and Babur Kocaoglu for research assistance.

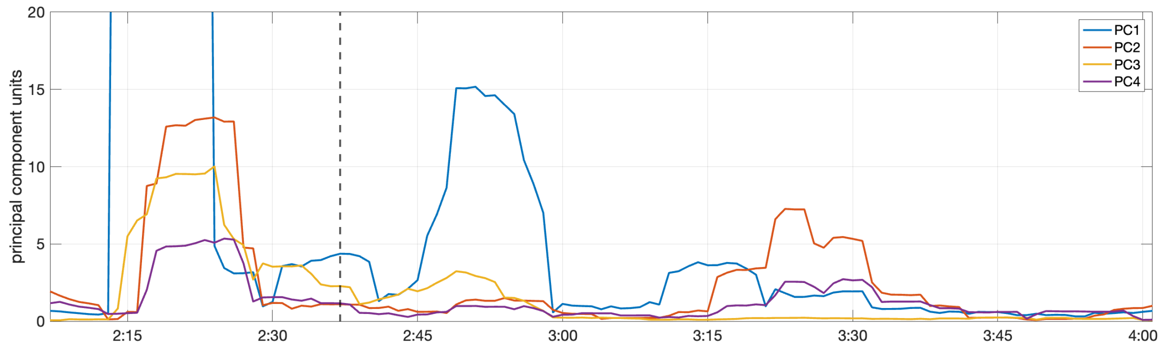
1 Introduction

Since Kuttner (2001), high-frequency movements in asset prices have been used to identify monetary policy shocks. However, the presence of multiple dimensions of policy complicates the task of identifying such shocks. Existing approaches either assume that each asset price responds only to a single shock over a certain window (e.g., Krishnamurthy and Vissing-Jorgensen (2011); Gertler and Karadi (2015)), or compute decompositions identified across announcement dates (e.g., Gürkaynak et al. (2005) (hereafter GSS); Swanson (2021); Rogers et al. (2018) (hereafter RSW); Nakamura and Steinsson (2018); Inoue and Rossi (2020)).

The former strategy either assumes the presence of a single shock or imposes exclusion restrictions across assets. Faced by unconventional policy at the zero lower bound (ZLB), this means that one price responds to target rate shocks and another to forward guidance shocks, for example. The latter strategy, pooling price changes across announcements and computing some time-invariant decomposition into structural shocks, follows the influential work of Nelson and Siegel (1987) and GSS. Shocks can differ across announcements only in scale, not in their relative impacts on different asset prices. For example, this means that the asset purchase shock prompted by the announcements of QE1 and QE2 must have the same impacts on all interest rates, despite targeting different securities. Assumptions are also needed to recover shocks with structural interpretations, since the statistical factors typically estimated are identified only up to orthogonal rotations. Swanson (2021) extends the approach of GSS to distinguish forward guidance and asset purchase shocks, combining exclusion and narrative restrictions. RSW impose a lower-triangular structure on futures corresponding to interest rates of various maturities. However, the challenge of central bank information shocks, highlighted by Jarociński and Karadi (2020), Lunsford (2020), and Miranda-Agrippino and Ricco (2021), but questioned by Bauer and Swanson (2022), remains unaddressed in models boasting the Fed Funds, guidance and asset purchase shocks.

I propose to identify *announcement-specific* decompositions of asset price movements to recover monetary policy shocks without assuming time-invariance across announcements. Instead of pooling data across announcements, I treat common movements in interest rates and equities following monetary policy announcements as responses to a series of monetary policy news shocks. This means that up to several hours of minute-by-minute data can be used to identify a decomposition unique to any announcement. Figure 1 plots 10-minute moving-averages of the squares of the first four principal components of a panel of asset prices following the March 18, 2009 announcement, when the Federal Open Market Committee (FOMC) strengthened forward guidance and expanded QE1. There are large movements in asset prices outside of the conventional 30-minute window, which indeed suggest the presence

Figure 1: Moving average of squared principal components on March 18, 2009



10-minute moving averages of squared principal components of a panel of 20 asset price changes on March 18, 2009, from the beginning of the conventional 30-minute window (10 minutes before the announcement) through 4:01pm, immediately following market close. The y-axis is truncated to highlight relevant variation. Plotting squared innovations to the principal components instead produces a plot with the same dynamics.

of a more continuous stream of monetary policy news, or at least the continued processing of previously-released news. This variation has yet to be exploited for identification.

I thus use intraday timeseries of asset price movements to identify up to four monetary policy shocks following a given announcement: a "Fed Funds" shock, a "forward guidance" shock, an "asset purchase" shock, and a "Fed information" shock.[1] The latter is missing from previous papers (e.g., Swanson (2021); RSW) that separately identify forward guidance and asset purchase shocks. To identify the shocks from these intraday timeseries, I adapt an identification argument based on time-varying volatility, developed in Lewis (2021). The volatility patterns evident in Figure 1 make such an approach natural.

For each FOMC announcement from 1996-2019, I extract principal components of 20 intraday asset prices following the announcement. I use a test proposed in Lewis (2021) to determine the maximum number of shocks identifiable based on time-varying volatility, before adopting the identification scheme from that paper, a generalized version of identification via heteroskedasticity. I thus recover intraday timeseries of that number of shocks – the unique rotation of the principal components that is consistent with the observed volatility dynamics. I use an information criterion to determine the number of these shocks that represent monetary policy shocks, discarding the remainder as noise. To measure the effects of monetary policy on interest rates and equities following an announcement, I compute historical decompositions with respect to the high-frequency shocks.

This framework is flexible in three important ways. First, I do not assume the nature

[1]While Kroencke et al. (2021) propose to identify a "risk shift" shock, which explains a greater share of announcement-window variation in the prices of risky assets, such a dimension is outside the scope of this paper.

of monetary policy shocks is the same from one announcement to the next, as implied by a constant decomposition (since relative effects of shocks on asset prices are fixed). There is little reason to think that asset purchase announcements targeting different securities should have identical effects on asset prices; Lunsford (2020) characterizes how forward guidance evolved during the early 2000s, with further evolution coming during the Great Recession. Second, even if the nature of shocks was constant over time, it is important to allow their relative impacts on asset prices to vary, since the relationship between news and the public's expectations of the state variables in the economy may either be nonlinear, or otherwise change over time, as argued by Faust et al. (2007). Finally, I do not require all shocks to be active for each announcement, an important consideration when identifying several dimensions of policy. This is particularly important, since asset purchase policies were not in effect for the majority of the sample, yet arguably were a defining feature of monetary policy at the end of the sample. This framework, which could easily be adapted to other types of announcements, like macroeconomic releases or corporate news, is the methodological contribution of this paper.

I use the historical decompositions of interest rates and equities to compare the effects of key monetary policy announcements during the Great Recession. This comparison is possible and meaningful because I have not assumed the relative effects of each shock to be constant from one announcement to the next. My methodology combines attractive features of several existing papers: the announcement-by-announcement comparison of the event-studies of Krishnamurthy and Vissing-Jorgensen (2011) and the ability to disentangle forward guidance and asset purchase shocks (with the addition of Fed information shocks) from Swanson (2021) and RSW. I find that few monetary policy announcements sparked significant shocks, but those that did can be characterized as the introduction of new policies or the unexpected extension of existing policies. This marriage of carefully-measured shocks with the narrative record is the second contribution of the paper.

I next form a timeseries of the four monetary policy shocks, measured by historical decompositions, and use them to estimate the responses of key financial variables. Contractionary forward guidance and asset purchase shocks both raise corporate yields and uncertainty and lower corporate spreads. Fed information shocks raise yields and lower uncertainty. These results mirror existing papers including Krishnamurthy and Vissing-Jorgensen (2011), Swanson (2021), and Campbell et al. (2012), but establishing them jointly with those for Fed information shocks constitutes a third contribution of this paper.

Finally, I use the timeseries to estimate the macroeconomic effects of the different dimension of monetary policy. While Swanson (2021) and RSW disentangle forward guidance and asset purchase shocks, neither studies the impact on the real economy. Across the full sample, Fed Funds, forward guidance, and asset purchases all have significant, persistent effects on inflation, unemployment, and industrial production in the direction predicted by theory. During the Great Recession, asset purchases had stronger effects, and the impact of forward guidance was attenuated. The results are quite similar to what one would obtain using the Swanson (2021) shocks, but starkly different to those based on the RSW shocks. I additionally find that Fed information shocks predict positive economic developments, particularly after 12 months. These findings, characterizing the real effects of unconventional monetary policy, are the final contribution of the paper.

Cieslak and Schrimpf (2019) is, to my knowledge, the only other paper to examine intraday comovements of yields and stock prices by announcement to characterize monetary policy news, but simply classifies each announcement as belonging to one of four discrete categories, rather than decomposing movements into different components. On the other hand, Jarociński (2022) recently identifies the same quartet of shocks as I do, but using a time-invariant decomposition and a different form of statistical identification, exploiting kurtosis of the shocks. Although previous papers analyzing the effects of unconventional policy on macroeconomic aggregates have not jointly identified forward guidance and asset purchase shocks, especially in the presence of Fed information effects, a growing literature does exist. Baumeister and Benati 2013, Gambacorta et al. (2014), and Lloyd (2018) identify a range of asset purchase-related shocks ("spread compression"; "balance sheet"; "signaling" and "portfolio balance", respectively) in VARs using sign and exclusion restrictions. Baumeister and Benati (2013) allow for the time-varying nature of shocks, using a time-varying parameters model, as does Paul (2020), although he only estimates the effects of the Fed Funds shock. The findings of Gambacorta et al. (2014) for their balance sheet shock and those of Bundick and Smith (2020) for forward guidance align well with the significant macroeconomic effects I estimate. Inoue and Rossi (2020) estimate local projections for two policy dimensions corresponding to the slope and curvature factors from a Nelson and Siegel (1987) decomposition, but these are not interpretable as particular dimensions of unconventional policy.

The remainder of the paper is organized as follows. Section 2 discusses the identification problem in more detail and outlines my approach. Section 3 presents announcement-specific results, discussing the findings for notable FOMC announcements in detail. Section 4 describes the timeseries of monetary policy shocks and computes the responses of financial markets and macroeconomic aggregates to the measures. Section 5 concludes.

2 Intraday identification of monetary policy shocks

In this section, I motivate the use of announcement-specific decompositions and argue that they can, in principle, be identified using intraday data. I then discuss how time-varying volatility can be used to do so. Finally, I describe my empirical approach.

2.1 The case for intraday identification

High-frequency identification of monetary policy shocks draws on the event-study methodology of empirical finance, as described by Campbell et al. (1997). Those authors write abnormal returns, $\eta_{it,\delta}$, for security i from $t-\delta$ to t as

$$\eta_{it,\delta} = R_{it,\delta} - E\left[R_{it,\delta} \mid \mathscr{I}_{t-\delta}\right], \tag{1}$$

where $R_{it,\delta} = P_{it} - P_{it-\delta}$ and $\mathscr{I}_{t-\delta}$ is the information set available at $t-\delta$, with $t, t-\delta \in [0,1]$ indexing time-points during the day. In typical studies of monetary policy shocks, $E\left[R_{it,\delta} \mid \mathscr{I}_{t-\delta}\right] = 0$, so $\eta_{it,\delta} = R_{it,\delta} = P_{it} - P_{it-\delta}$. If markets price all new information immediately, then the change over the window $t-\delta$ to t represents all news during that window. Monetary policy news can thus be measured as the change in an interest rate future, Treasury yield, or some basket of such asset prices over an interval $[t-\delta, t]$ containing the announcement, often 10 minutes prior to the announcement to 20 minutes following. This measure can either be used directly (following Kuttner (2001)) or as an instrument for a latent monetary policy shock (e.g., Gertler and Karadi (2015)).

However, if there are multiple dimensions of monetary policy, and thus multiple simultaneous monetary policy shocks, $\epsilon_{jt,\delta}$, they must be recovered in some way from an $n \times 1$ vector of abnormal returns, $\eta_{t,\delta}$:

$$\eta_{t,\delta} = H\epsilon_{t,\delta},$$

where $\epsilon_{t,\delta}$ is typically $n \times 1$ and H is invertible. If exclusion restrictions are available, such that for each shock j there exists some asset i that responds only to shock j, or if only one dimension of policy is active at one time (the approach implicit in Krishnamurthy and Vissing-Jorgensen (2011)), then monetary policy shocks can still be read as simple asset price changes for each announcement. However, those are strong assumptions, particularly during the ZLB period. Following GSS, it is more common to attempt to recover $\epsilon_{t,\delta}$ by pooling information across announcements to estimate moments of $\eta_{t,\delta}$, which can then be used to identify the decomposition, H. In particular, the econometrician works with

$$\eta_d = H\epsilon_d, d = 1, \ldots, D, \tag{2}$$

where η_d is the return $\eta_{t,\delta}$ on announcement date d and similarly $\epsilon_d \equiv \epsilon_{t,\delta}$ for day d. While second moments of (2) can now be estimated and used for identification, they provide only $(n^2 + n)/2$ identifying equations in n^2 unknowns, so further assumptions are still required (typically exclusion restrictions, as in GSS; Swanson (2021); RSW; Campbell et al. (2012); Nakamura and Steinsson (2018)).

However, the problem posed by (2) already makes a strong assumption: H must be constant from one announcement to the next. Implicitly, the nature of the shocks, ϵ_d, must not change – otherwise there is little reason to assume constant relative effects, H, on η_d. Indeed, during the Great Recession, the character of shocks *did* change from one announcement to the next. Forward guidance evolved from vague to calendar-based to conditional, and the composition of asset purchases varied between mortgage-backed securities (MBS) and Treasuries, as well as in the maturities targeted. Moreover, even if the nature of the shocks were fixed, Faust et al. (2007) argue that the linear relationship between news shocks and asset prices in (2) almost certainly changes from one announcement to the next. They explain that the coefficients in H represent a weighted average of the changes in expectations of all relevant state variables in response to ϵ_d, where the weights are the derivative of asset prices η_d with respect to each state variable. H will be constant if and only if both the relationship between (market expectations of) all state variables and all shocks is linear and asset prices are a linear function of all state variables. Thus, even if the mapping between shocks and asset prices is constant, H will be time-varying in the face of non-linearities in state variables and expectations. Not only does fixing H embed strong assumptions on the nature of shocks and linearity, it also precludes potentially interesting questions of how the effects of monetary policy shocks varied from one announcement to the next. Whether the assumption of constant H impacts results is worth investigating.

I address these concerns with a novel methodology. Rather than only examining a single change in asset prices (from $t - \delta$ to t) on each announcement date, I consider the path of asset prices following an announcement to represent responses to a stream of monetary policy news. Such news may either be new information revealed by the Federal Reserve (in the FOMC statement or during a press conference), a delayed interpretation of existing information (unpacking the implications of a change in forward guidance may take time), or an innovation to the interpretation of previous news (perhaps in light of the response of other agents). This re-framing of the problem provides an intraday timeseries for each announcement that may be used to estimate moments and identify an announcement-specific decomposition. In particular, for announcement d, I propose to study the model

$$\eta_m = H_d \epsilon_m, \; m = 1, \ldots, M, \tag{3}$$

where η_m are high-frequency returns from $(m-1)/M$ to m/M over the period running from 10 minutes prior to the announcement until market close, which I normalize to length 1. H_d is the *announcement-specific* relationship between asset prices and shocks. Using a window extending to market close accounts for additional news or revision of initial reactions during or following press conferences. Combined with a credible identification scheme, the model (3) can recover a mapping between asset prices and monetary policy shocks unique to any announcement, d. This insight is not limited to the study of monetary policy; the methodology can be adapted to study any type of news shocks using suitable financial data.

The sample length in (3) is fixed: it runs from 10 minutes prior to the announcement until market close. This makes a large$-T$ asymptotic framework ill-suited. Rather, a continuous time model for ϵ and an infill asymptotic framework are more appropriate given the use of high-frequency financial data (see, e.g., Barndorff-Nielsen and Shephard (2002); Andersen et al. (2003)). I adopt a simplified multivariate version of the standard continuous time model of Barndorff-Nielsen and Shephard (2002) for $t \in [0,1]$, with instantaneous returns, $\eta(t)$, given by

$$dP(t) = \eta(t) = H_d \epsilon(t), \tag{4}$$

and instantaneous structural shocks $\epsilon(t)$ following the stochastic differential equation

$$\epsilon(t) = diag(\sigma(t))\, dW(t), \tag{5}$$

where $\sigma(t)$ is the instantaneous (spot) volatility and $W(t)$ is an n dimensional standard Brownian motion. In this setting, structural shocks ϵ_m are defined on a $1/M-$spaced grid,

$$\epsilon_m = \epsilon^*(m/M) - \epsilon^*((m-1)/M), m = 1, \ldots M, \tag{6}$$

where

$$\epsilon^*(t) = \int_0^t \epsilon(u)\, du = \int_0^t diag(\sigma(u))\, dW(u).$$

It follows that

$$\epsilon_m \mid \sigma_m^2 \sim N\left(0, diag\left(\sigma_m^2\right)\right),$$

where

$$\sigma_m^2 = \sigma^{2*}(m/M) - \sigma^{2*}((m-1)/M) \text{ and } \sigma^{2*}(t) = \int_0^t \sigma^2(u)\, du.$$

This model does not explicitly incorporate jump behavior in asset prices (although $\sigma(t)$ is unspecified), but, as discussed below, I work with innovations to the common component of asset prices, which I find do not generally exhibit jumps, even if the raw prices do.

While the idea of studying the high-frequency mapping H_d is novel, there is a close relationship between H_d and its event-study counterpart. In particular, let H_d^{inf} be the announcement-specific parameter infeasibly identified from hypothetical *repeated samples* of

$$\eta_d = H_d^{inf} \epsilon_d,$$

for a single day, d, using some valid identification scheme. Proposition 1 relates H_d to H_d^{inf}:

Proposition 1. *Under the model described by (4) and (5), H_d^{inf}, infeasibly identified from repeated samples of η_d, is identical to H_d.*

This result shows that under the continuous time model described above, the announcement-specific high-frequency response matrix, H_d, is equivalent to the desired, but infeasibly-identified, event-study parameter for a given day. However, H_d can be feasibly recovered.

2.2 Identification via time-varying volatility

I have argued that H_d can in principle be identified from intraday data, but it remains to propose a suitable identification scheme to do so. The same intuition and arguments used for the conventional SVAR setting can still be applied, simply making reference to the infill analogs of large$-T$ moments. Indeed, given that actual observations remain discrete (and evenly spaced), in practice unmodified estimators can be applied to the intraday observations, just as they would be in traditional data (see Supplement B).

It is unappealing to impose assumptions on H_d (exclusion or sign restrictions) since H_d is the object of interest and because it is hard to argue that some asset prices systematically respond more slowly to forward guidance, asset purchase, or Fed information shocks, for example. The Swanson (2021) narrative approach to distinguish forward guidance and asset purchase shocks, based on the absence of asset purchase shocks prior to 2009, is not applicable after 2009 given all shocks come from a single announcement day.

These factors lead me to consider statistical identification, in particular identification based on time-varying volatility. Figure 1 demonstrates strong volatility patterns for an example announcement date. Identification via heteroskedasticity has proven popular for identifying asset price responses to news and policy shocks, as proposed by Rigobon (2003), and implemented by Rigobon and Sack (2003), Rigobon and Sack (2004), and Gürkaynak et al. (2020), for example. Previous approaches exploiting heteroskedasticity for identification have largely relied on externally-specified variance regimes or highly specific functional forms for the volatility process that facilitate identification (e.g., GARCH). Lewis (2021) provides an entirely non-parametric identification argument based on time-varying volatility in a large$-T$ framework, generalizing existing results. I reframe the argument below for the infill framework, sketching intuition in a simple case and stating the general identification result; further details can be found in Lewis (2021).

An important distinction given the infill context is that identification is a property of population moments. In an infill setting, the analog to infinite sample size is an arbitrarily fine $1/M$ grid of observations, converging to the continuous time process, $\eta(m/M)$. Thus, identification conditions apply to the underlying continuous time processes, although observations are discrete. In Supplement B, I show that simple sample averages of squared returns can be consistent for these identifying moments of the underlying continuous time processes.

I henceforth suppress the d subscript on H_d for compactness, since each day's data forms a unique dataset. Assumption 1 imposes standard assumptions on H and $\sigma^2(t)$.

Assumption 1. *For $t \in [0,1]$,*

1. *H is fixed, full-rank, and has a unit diagonal,*
2. *$\sigma^2(t)$ is an $n \times 1$ stationary stochastic process, has almost surely locally square integrable sample paths, and is independent of $W(t)$, with $E\left[\sigma^2(t)\sigma^2(t)'\right] < \infty$.*

The first assumption is standard in models of the form (2) or (4). $\sigma^2(t)$ is required to be independent of the structural shocks (common in continuous time settings, even those accommodating ARCH effects, e.g., Brockwell et al. (2006)) and to have finite moments. The model (5) already imposes orthogonality and a martingale difference sequence (MDS) property for the structural shock processes and finite moments of the driving process, $W(t)$. As discussed in Lewis (2021), stationarity is not required for identification, but I impose it here since it simplifies the derivation of limiting moments of η_m in terms of the underlying continuous time process $\sigma^2(t)$. These assumptions imply that ϵ_m is also vector of orthogonal MDSs (with respect to σ_m^2 and information through $(m-1)/M$) with conditional variances σ_m^2 and finite fourth moments, satisfying the requirements in Lewis (2021).

Lewis (2021) argues that the autocovariance of squared innovations, η_m, can be used to identify H. To build intuition, consider a simple case where $n = 2$, and the variance of the first shock, $\sigma_1^2(t)$, is constant, $\sigma_1^2(t) \equiv \sigma_1^2$. Let H_{12} be the parameter of interest. Note that taking the outer product of reduced-form innovations, η_m, yields

$$\begin{aligned}\eta_{1m}\eta_{2m} &= H_{21}\epsilon_{1m}^2 + H_{12}\epsilon_{2m}^2 + \epsilon_{1m}\epsilon_{2m} + H_{12}H_{21}\epsilon_{1m}\epsilon_{2m} \\ \eta_{2m}^2 &= H_{21}^2\epsilon_{1m}^2 + 2H_{21}\epsilon_{1m}\epsilon_{2m} + \epsilon_{2m}^2.\end{aligned}$$

It is clear that H_{12} could be identified from the ratio of the $H_{12}\epsilon_{2m}^2$ and ϵ_{2m}^2 terms, but only the values of η_m are observed, and not their separate components. However, a lagged value of η_{2m}^2 can be used as an instrument for ϵ_{2m}^2. In particular, using the orthogonality and zero serial correlation of shocks and the fact that σ_1^2 is constant (so has zero autocovariance),

$$\text{cov}\left(\eta_{1m}\eta_{2m}, \eta_{2(m-pM)}^2\right) = H_{12}\text{cov}\left(\epsilon_{2m}^2, \epsilon_{2(m-pM)}^2\right), \quad \text{cov}\left(\eta_{2m}^2, \eta_{2(m-pM)}^2\right) = \text{cov}\left(\epsilon_{2m}^2, \epsilon_{2(m-pM)}^2\right).$$

The lag is specified as pM so that the time distance between observations m and $m - pM$ remains fixed as $M \to \infty$. As shown in Supplement B.1, $\lim_{M\to\infty} M^2\text{cov}\left(\epsilon_{2m}^2, \epsilon_{2(m-pM)}^2\right) = \text{cov}\left(\sigma_2^2(t), \sigma_2^2(t-p)\right)$. Then, H_{12} is identified as

$$\frac{\lim_{M\to\infty} M^2\text{cov}\left(\eta_{1m}\eta_{2m}, \eta_{2(m-pM)}^2\right)}{\lim_{M\to\infty} M^2\text{cov}\left(\eta_{2m}^2, \eta_{2(m-pM)}^2\right)} = \frac{H_{12}\text{cov}\left(\sigma_2^2(t), \sigma_2^2(t-p)\right)}{\text{cov}\left(\sigma_2^2(t), \sigma_2^2(t-p)\right)} = H_{12}.$$

This is an instrumental variables approach, where the dependent variable is $\eta_{1m}\eta_{2m}$, the endogenous regressor is η_{2m}^2, and the instrument is $\eta_{2(m-pM)}^2$. Provided that the time-varying volatility $\sigma_2^2(t)$ is persistent ($\text{cov}\left(\sigma_2^2(t), \sigma_2^2(t-p)\right) \neq 0$ for some lag p), identification holds.

Of course, this example is simplified to recover H_{12} in closed-form. However, the intuition extends to the general model described in Assumption 1. Define $\zeta_m = vech\left(\eta_m\eta_m'\right)$, unique elements of the outer product of innovations. Theorem 1 states the identification result.

Theorem 1. *H is uniquely determined (up to column order) from $\lim_{M\to\infty} ME\left[\zeta_m\right]$ and $\lim_{M\to\infty} M^2 cov\left(\zeta_m, \zeta_{m-pM}'\right)$, if at least $n-1$ shocks display time-varying volatility with non-zero autocovariance, provided that for no two shocks i, j, $cov\left(\sigma_i^2(t), \sigma^2(t-p)'\right) = cov\left(\sigma_j^2(t), \sigma^2(t-p)'\right)\frac{E\left[\sigma_i^2(t)\right]}{E\left[\sigma_j^2(t)\right]}$.*

Theorem 1 follows from Corollary 2 in Lewis (2021) and infill limits derived in Supplement B.1. The condition that $n-1$ shocks must exhibit heteroskedasticity mirrors that for all other approaches based on heteroskedasticity, and indeed arguments based on higher moments in general. The final proportionality assumption is a rank condition guaranteeing the autocovariances provide linearly independent information. Lewis (2021) details a Cragg-Donald rank test for these identification conditions; testability has proven challenging for previous heteroskedasticity-based arguments. Identification holds up to column order – permutations of the columns of H are observationally equivalent. However, assigning labels to the structural shocks pins down a column permutation. It is also important to distinguish these results from simply computing principal components of η_m. Principal components satisfy second-moment equations that provide only enough information for uniqueness up to arbitrary orthogonal rotations, but the identification argument above recovers the unique decomposition of η_m that additionally respects the dynamic properties of the shock variances.

In the context of unconventional monetary policy shocks, the identification condition can be motivated economically. It makes sense that shock variances are heteroskedastic: volatility should increase around an announcement, as the FOMC statement is first published. This is a "first reading" of basic details – a change to the Fed Funds target rate, or a new round of asset purchases. However, this volatility likely dissipates, as less new information is available to be incorporated into asset prices. Nevertheless, volatility likely remains elevated, as markets continue to process the implications of details and wording of the FOMC statement, or in the presence of a press conference. Thus, it is natural that the volatilities of each monetary policy shock have some persistence. One way that the rank condition is satisfied is if each shock's own volatility is a stronger predictor of its future volatility than is the current volatility of other shocks. This makes sense, since a large amount of news in one dimension (prompting high volatility shocks) likely means a prolonged period of volatility in that shock, as markets continue to unpack the relevant information (or as questions in a press conference focus on a particular aspect of policy). On the other hand, the presence of much new information for markets to process about forward guidance does not necessarily imply there is so much to learn about asset purchases. If a shock's own volatility matters more for predicting its future values, then the autocovariance structure will be full-rank.

The identification argument, as presented in Lewis (2021), is entirely non-parametric; although I illustrate it here in the standard context of a Gaussian driving process, $\sigma^2(t)$ is left unspecified. While this non-parametric character justifies non-parametric estimators, it also frees the econometrician to choose from almost arbitrary parametric volatility models, including many incompatible with previous approaches to identification based on heteroskedasticity. Among these are state space models, and in particular stochastic volatility models, which have proven very popular for modeling financial returns (see e.g., Shephard (1996) for an early review). However, prior to the argument in Lewis (2021), it had not been proven that such models could be used to exploit the identifying information offered by heteroskedasticity. Moreover, in a simulation study, Lewis (2021) finds that an estimator based on a first-order autoregressive (AR(1)) SV model performs best out of a wide range of non-parametric and previously-proposed parametric estimators based on heteroskedasticity, proving robust to misspecification of the volatility process. For these reasons, and given the long history of the model in modeling asset prices, I adopt the AR(1) SV estimator to implement identification based on time-varying volatility in the present paper.

2.3 Empirical model

The previous sections make a case for identifying announcement-specific decompositions of asset prices into monetary policy shocks, and for using time-varying volatility to identify such decompositions. I now lay out the specific empirical model I adopt for each intraday dataset and highlight the important features of my approach.

Identifying intraday shocks

I use a panel of 20 asset prices. Minute-by-minute data, Y_m, consist of the first 6 months of Fed Funds futures contract rates, the first 8 quarters of Eurodollar (ED) contract rates, 3-month, 6-month, 2-year, 5-year, and 10-year Treasury yields, and the log of the S&P 500, very similar to the dataset considered by Swanson (2021).[2] My first step to minimize the role of microstructure noise is to take as my observations the bid-ask midpoints for each price; doing so eliminates bid-ask "bounce", which Aït-Sahalia and Yu (2009) find is possibly the most important component of such noise. I take first differences, ΔY_m, standardize to $\Delta\tilde{Y}_m$, and then estimate the first four principal components, F_m, of the data from 10 minutes prior to the announcement to 4:01pm, immediately following market close,

$$\Delta\tilde{Y}_m = \Lambda F_m + u_m,\ m = 1, \ldots, M.$$[3]

I recover the first four components to span up to four possible dimensions of monetary policy shocks. Working with the first few principal components of the individual asset prices further reduces the threat of microstructure noise. Several sources of microstructure noise, like bid-ask bounce and discreteness of possible price changes, are inherently idiosyncratic and need not be correlated across observed prices. Other sources, like differences in trade sizes or informational content of price changes, as well as strategic aspects of the order flow, could simultaneously impact related interest rates. However, even if there is some common component to microstructure noise, results in Aït-Sahalia and Yu (2009) suggest that, at least for liquid assets, like those in my panel, microstructure noise is considerably smaller than fundamental volatility, which would make it unlikely to appear in the first few principal components. Relative to focusing on a small number of representative interest

[2]While Swanson (2021) does not include all maturities in the panel to estimate his factors due to high mechanical correlation for technical reasons, the correlations across contract rates and yields are much weaker at minute-frequency, as opposed to Swanson's 30-minute windows, so the role of mechanical correlation appears lower. However, the value of a large panel is higher when noise is larger, as in minute-frequency data. I include the S&P 500 in my estimation panel to help identify Fed information shocks.

[3]Following Nakamura and Steinsson (2018), for announcements included in the GSS sample, I use the announcement times from their data Appendix. For later announcements, I use the timestamp of the first headline appearing on Bloomberg's news archive.

rates, working with principal components also decreases the likelihood of mischaracterizing the overall movement of Treasury yields when various maturities move in opposite directions following announcements. F_m forms the data for subsequent analysis.

For each announcement of the 199 scheduled and unscheduled announcement dates in my sample, I build my empirical model recursively, starting from $n = 4$ principal components, until I find a model for which n shocks may be identified by time varying volatility:[4]

1. Set $n = 4$.
2. Estimate a VAR for the first n principal components to remove any residual predictability from the series (since ϵ_m must be a MDS), using the Hannan-Quinn information criterion to select L:
$$F_m = b + \sum_{l=1}^{L} B_l F_{m-l} + \eta_m. \tag{7}$$
3. Test whether the condition for identification by time-varying volatility is satisfied for the residuals, $\hat{\eta}_m$, using the test proposed in Lewis (2021). In particular, I test whether
$$rank\left(E\left[\hat{\zeta}_m \hat{\zeta}'_{m-1}\right]\right) = n,$$
where $\hat{\zeta}_m = vech\left(\hat{\eta}_m \hat{\eta}'_m\right)$, which indicates that the autocovariance process of σ^2_m is full rank, satisfying the condition in Theorem 1.
4. If the test is satisfied, proceed to step 5; otherwise, return to 2, replacing n with $n-1$.
5. Set $k_s = n$, the number of identifiable shocks. Implement the AR(1) SV estimator developed in Lewis (2021) to estimate H and the k_s intraday shocks, ϵ_m, from the VAR in the first k_s principal components.

Figure 7 in the Supplement summarizes the lag lengths and the explained variation (R^2) for the reduced-form VARs in the principal components, step 2. The median lag length is 2, and ample unpredictable variation remains in the innovations. The parametric form of the estimator adopted in Step 5 has been found to fit financial data well (see e.g., Shephard (1996), Kim et al. (1998)). While asset prices may exhibit jumps around FOMC announcements, calling into question whether this model is appropriate, I find that the principal components of asset prices, F_m, exhibit much smoother behaviour than the raw prices, and the innovations η_t I ultimately work with are smoother still. Simulations in Lewis (2021) find the AR(1)

[4]Note that while there are 202 announcements between 1996 and 2009, there are three announcement dates relatively early in the sample, July 1 1998, April 18 2001, and August 21 2001, for which raw data available from Eikon DataScope Select is missing. I have no choice but to drop these announcements from my sample.

SV estimator to be robust to misspecification of the volatility process. While the procedure to estimate the shocks is more computationally intensive than a typical identification scheme based on a single pooled sample of data, nearly all computation time is spent estimating the state-space model in step 5 across a grid of start values, which can be trivially parallelized.[5]

Labelling and measuring the monetary policy shocks

The next step is to determine the number of monetary policy shocks active on a given day, k_{mp}. I assume that k_{mp} equals the dimension of the common component, the number of principal components driving the panel of asset prices jointly, as opposed to capturing idiosyncratic noise. I estimate the dimension of the common component, k_{mp}, using the BIC_2 information criterion of Bai and Ng (2002).[6] Prior to December 2008, when asset purchases were first mentioned in an FOMC statement, I consider candidate values $1 \leq k_{mp} \leq 3$, and from December 2008 onwards I consider $1 \leq k_{mp} \leq 4$. I estimate the model dimension, k_s, separately from the dimension of monetary policy, k_{mp}, to first ensure the dimension of the volatility process is actually adequate to identify the required number of monetary policy shocks and second to potentially further reduce the role of (microstructure) noise. In particular, $k_s \geq k_{mp}$ ensures that shocks to all dimensions of monetary policy can indeed be identified (since *ex ante* innovations to the common component could be purely homoskedastic) and allows the possibility that additional non-monetary policy shocks also enter the *innovations* to the principal components, η_m (even those to the first k_{mp} components). Thus, I determine k_s, the number of shocks identifiable via time-varying volatility, and estimate a model including that number of shocks to allow me to potentially discard some of the variation in the innovations η_m as noise. In other words, estimating a model of weakly larger dimension than k_{mp} is a check on any possible non-invertibility arising from additional, non-monetary policy noise entering the equations for η_m. The shocks that are least compatible with the theoretical economic properties of monetary policy shocks are the ones discarded, using the labeling criterion described below. For all announcements, I find that there are weakly more identifiable shocks than monetary policy shocks, $k_s \geq k_{mp}$; Figure 8 in the Supplement plots the values of both over time. Figure 9 in the Supplement reports forecast error variance decompositions (FEVDs), showing that noise shocks may explain considerable variation in η_m, illustrating the importance of accounting for such potential noise.

[5] After parallelization of start values (across 48 Intel(R) Xeon(R) Gold 6146 CPUs), decompositions can be estimated for all 199 announcements in about 2 hours and 15 minutes using Matlab 2020a.

[6] I also considered the remaining 5 information criteria of Bai and Ng (2002). The BIC_2 is the only information criterion to choose interior solutions.

To measure the shocks and their effects at conventional frequencies (windows), I use historical decompositions of Y_m with respect to each of the k_s shocks to aggregate the intraday shocks. I adapt the historical decompositions, as described in Supplement C, to account for the deterministic drift introduced by standardizing ΔY_m to $\Delta \tilde{Y}_m$ prior to taking principal components. Doing so allows the counterfactual paths to actually track the trajectory of Y_m.[7]

I label the shocks based on these historical decompositions. I label k_{mp} of the k_s identified shocks using a quantitative labeling criterion, which I describe in detail in Supplement D. For each possible combination of shocks and labels, I evaluate the criterion, and select the shock-label configuration most consistent with economic theory. This is the most economically-driven feature of the identification approach, and the separation of forward guidance and asset purchase shocks in particular hinges on these assumptions. The economic basis of my identification approach is as follows. Prior to December 2008, when an FOMC statement mentioned asset purchases for the first time, there is no asset purchase shock. I designate as Fed Funds shocks those that shift at least the first two Fed Funds futures contracts; even if such a shock also moves longer yields, priority is given to labeling it as a Fed Funds shock. I designate as forward guidance shocks those that shift at least the 6- through 8-quarter ED rates, (proxying for interest rate expectations near the 2-year horizon at which explicit forward guidance was generally targeted), while moving the S&P 500 in the opposite direction, characteristic of an "Odyssean" guidance shock. From December 2008 onwards, I label as asset purchase shocks those that shift at least one of the 5- and 10-year Treasury yields, while moving the S&P 500 in the opposite direction. The fact that I can flexibly characterize asset purchases in this way is an advantage of my approach; allowing asset purchase shocks to potentially move Treasury yields of different maturities to differing degrees or directions reflects the targeted nature of many such announcements. Finally, Fed information shocks are those that move the S&P 500 and interest rates in the same direction, as in Jarociński and Karadi (2020). The quantitative criterion approach described in Supplement D helps operationalize these intuitive characterizations of the shocks and determine labels when multiple shocks match the features of a single label, or vice versa.

While it is true that the differentiation between forward guidance shocks and asset purchase shocks is a partition of the yield curve, this is also true of RSW, for example. Moreover, I label the forward guidance shock not by its impact on shorter Treasury yields, but on Eurodollar rates around the 2-year horizon to focus specifically on expectations of short rates

[7] When reporting responses and decompositions of asset prices, I scale them for interpretability. For the front Fed Funds future, I use the factor described by GSS to account for days remaining in the contract month. For Treasury yields, I scale by the ratio of the constant-maturity Treasury yield at close to the value of the intraday timeseries at close to maintain comparability of maturities across announcements.

at the horizon at which most explicit forward guidance has been focused, as opposed to average expectations of future interest rates over the next two years. I additionally exploit the fact that asset purchase shocks may have non-uniform effects on the yield curve as a further distinguishing feature (while forward guidance should shift most rates/yields) and relative to RSW I allow asset purchase shocks to impact medium-term expected rates, consistent with the signaling channel (see, e.g., Krishnamurthy and Vissing-Jorgensen (2011)). Nevertheless, at no point does my labeling approach preclude that forward guidance shocks may impact the entire yield curve; however, to be designated as forward guidance, a shock must explain movements in Eurodollar rates around the 2-year maturity at least as well as it does longer Treasury yields. In further defense of this labeling approach, and in particular the separation of forward guidance and asset purchases, Figure 9 in the Supplement reports the averages across announcements of high-frequency FEVDs for the portion of asset prices explained by the principal components, with the results validating the labeling: forward guidance shocks explain considerable variation for both the 8-quarter ED rate and long Treasury yields, while asset purchases explain relatively little variation in the 8-quarter ED rate. Section 3.2 shows that the labeling of shocks matches the narrative record for key events very well. Additionally, regressing the end-of-day decompositions of the 8-quarter ED rate on the asset purchase shock series (following the exercise in Table 2 below) shows the effect is only significant at the 10% level (consistent with the signaling channel); for comparison, the $p-$value for the Fed information shock is 0.001, and the $p-$values for the effects of forward guidance shocks on Treasury yields are smaller still. Figure 3 shows that the time series paths of the shock series is qualitatively similar to those of both RSW and Swanson (2021). Moreover, Figure 15 in the Supplement shows that the impulse responses of various Treasury yields to my forward guidance and asset purchase shocks are very similar to those for the RSW and Swanson (2021) shocks. Finally, the local projections in Section 4.3 shows that the effects of my shocks on macroeconomic aggregates are quite similar to those of the Swanson shocks.

3 Announcement-specific decompositions

In this section, I present announcement-specific results. I summarize high frequency relationships between shocks and asset prices; even at such frequencies, the results are credible. I describe in detail the lessons historical decompositions illustrate for 12 key announcement dates and how those conclusions extend to the full set of 199 announcement dates. Finally, I outline heterogeneity in the relative impacts of the asset purchase shock across announcements, affirming the importance of announcement-specific decompositions. Throughout this section, I focus on the responses of 5 representative asset prices. In particular, I study the response of the front Fed Funds future rate, the 8-quarter ED rate, the 5- and 10-year Treasury rates, and S&P 500 returns.

3.1 High frequency relationships

I first summarize (across announcements) the contemporaneous response of asset prices, Y_m, to monetary policy shocks ϵ_m, at minute-by-minute frequency. Such high-frequency responses are not of macroeconomic interest in their own right, but the results I obtain largely align with economic theory, and thus bolster the credibility of the following analysis. I measure the contemporaneous responses to shock j as $D(\sigma_{\Delta Y})\,\Lambda_{1:k_s}H_j$, where H_j is the column of H corresponding to the shock labeled as j (Fed Funds, etc.) and $D(\sigma_{\Delta Y})$ is the diagonal matrix with $\sigma_{\Delta Y}$, the standard deviation of ΔY_m, on the diagonal. For interpretability, I normalize responses by the percentage point change in the front Fed Funds future rate for the Fed Funds shock, the 8-quarter ED rate for the forward guidance shock, the 10-year Treasury yield for the asset purchase shock, and the S&P 500 for the Fed information shock. Table 1 reports the median response to each shock across all 199 announcements. The results show that, on average, even at such high frequency, a positive Fed Funds shock raises medium-term expectations of short rates (8-quarter ED) and medium to long Treasury yields, and lowers the S&P 500, in line with theory. A positive forward guidance shock has on average zero effect on expectations of the current Fed Funds rate, strongly raises Treasury yields, and lowers the S&P 500, as predicted for "Odyssean" guidance. A positive asset purchase shock has no effect on current Fed Funds expectations, raises medium-term expectations of short rates (the signaling channel) and Treasury yields, and lowers the S&P 500. Finally, a Fed information shock has no effect on current Fed Funds expectations, but raises medium-term expectations of short rates and Treasury yields with the S&P 500, as theory predicts. While these characteristics may be imposed on historical decompositions for the purpose of labeling the shocks, they are never required of the intraday shocks themselves. The scale of some effects may appear large, particularly for the S&P 500; however, the magnitude of the average high-frequency elasticity is not comparable to that of conventional event-study regression results (e.g., Kuttner (2001); Gürkaynak et al. (2005); Swanson (2021)).[8] Table 2 presents the relevant results for such comparisons.

[8]Despite the results of Proposition 1, the aggregation and averaging underlying Table 1 is not analogous to inter-announcement regression analysis.

Table 1: Contemporaneous responses of asset prices to high-frequency shocks

	FF	FG	AP	FI
$FF1$	1.00	0.00	0.00	0.00
$ED8$	0.10	1.00	0.68	1.08
$T5$	0.02	0.93	0.98	0.91
$T10$	0.04	0.71	1.00	0.76
SPX	-9.60	-34.59	-29.93	1.00

Each column reports the median across 199 announcements of $D(\sigma_Y)\,\Lambda_{1:k_s}H_j$, where H_j is the column of H corresponding to the shock (if any) labeled as j (Fed Funds, etc.). Responses are normalized by the percentage point change in the front Fed Funds future rate for the Fed Funds shock, the 8-quarter Eurodollar rate for forward guidance, the 10-year Treasury yield for asset purchases, and the S&P 500 for Fed information.

3.2 Historical decompositions

Major unconventional policy announcements during the Great Recession

I now present historical decompositions for 12 key monetary policy announcements during the Great Recession. These announcements match those detailed in Table 1 of Swanson (2021), with the addition of December 2008, when rates hit the ZLB for the first time, and details of asset purchases were provided, and March 2015, which contained explicit guidance about the timing of lift-off from the ZLB. Table 4 in Supplement E.2 details the content of these announcements. A unique feature of my approach is that I can meaningfully compare the decomposition of asset price movements into monetary policy shocks across these announcement dates. In all comparable methodologies, the relationship is fixed over time. For each date, I plot the decompositions of asset prices with respect to monetary policy shocks in Figure 2. A blue line denotes the Fed Funds shock, red forward guidance, gold asset purchases, and purple Fed information. For reference, I plot the observed path of the relevant asset price with a dashed line. Decompositions begin 10 minutes prior to the announcement; I indicate the timing of the announcement and 20 minutes following, the end of the conventional 30-minute event study window, with dashed lines. Frequentist inference on historical decompositions is not possible, since it would require inference on individual realizations of structural shocks, which are random variables, not parameters. Instead, I present a measure of "economic significance", based on the average (across announcement dates) standard deviation of the relevant interest rate in the hours following monetary policy announcements. The shaded interval corresponds to 1.96 such standard deviations.

The December 2008 announcement brought the Fed Funds rate to the ZLB for the first time. Accordingly, Figure 2 shows the Fed Funds shock significantly lowered all interest rates. The guidance implicit about future rates also had significant effects on the 8-quarter

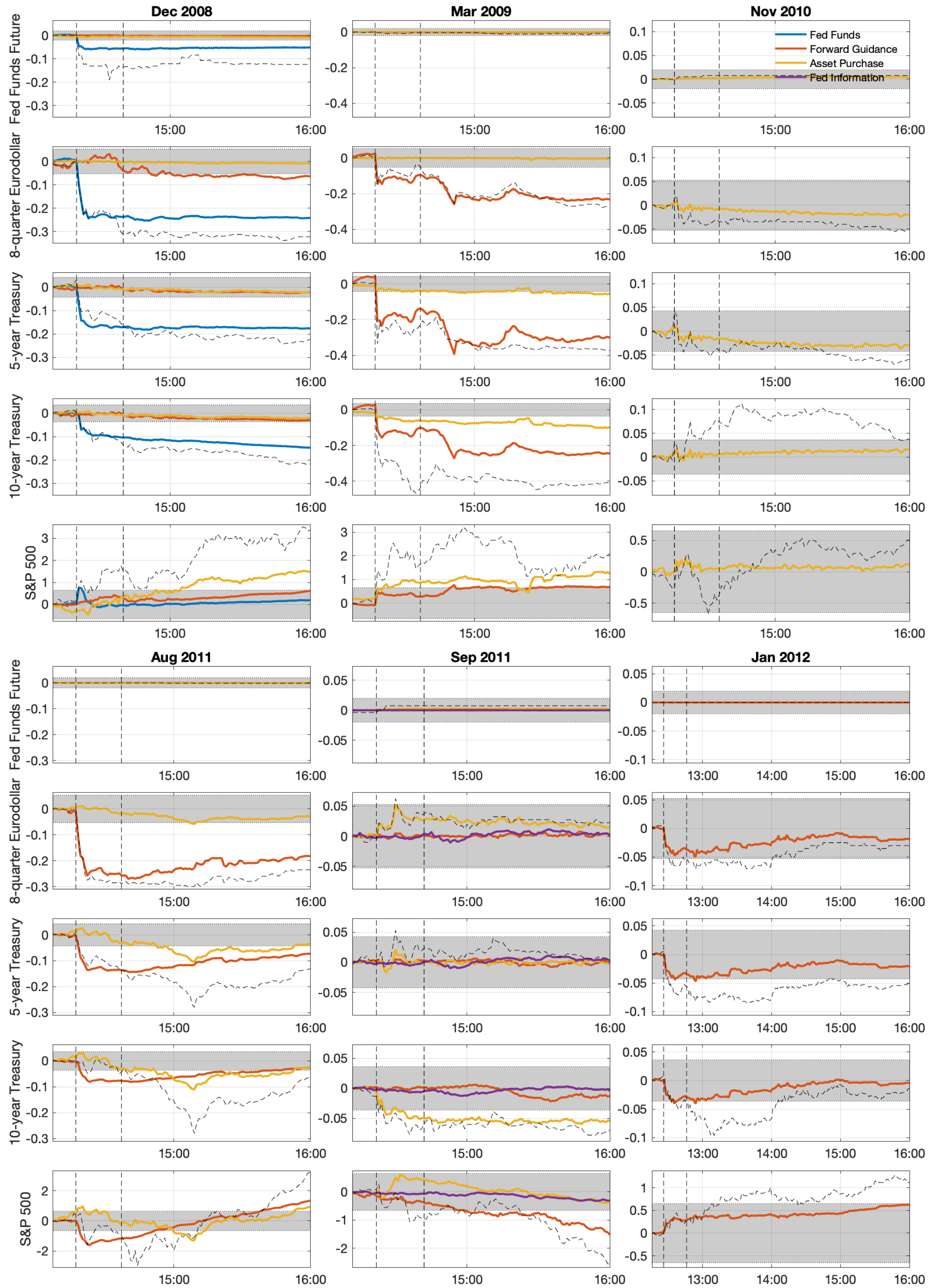
ED rate. The purchases of agency debt announced (with the suggestion of Treasury purchases to follow) had an insignificant impact on Treasury yields, but did raise S&P 500 returns. This decomposition suggests that the finding in Krishnamurthy and Vissing-Jorgensen (2011) that this QE1 announcement (containing little new information) had large effects on Treasury yields may be due to their event-study not accounting for the effects of the Fed Funds shock. The March 2009 announcement is one of the most notable of the sample, strengthening forward guidance and detailing purchases of mortgage-backed securities (MBS), long-term Treasuries, and agency debt (QE1). Accordingly, the forward guidance shock significantly lowered all longer rates, the asset purchase shock significantly lowered Treasury yields, and both significantly boosted the S&P 500. The November 2010 announcement introducing further purchases of longer-term Treasuries, QE2, failed to register a significant effect on any variable. However, this announcement illustrates the need for announcement-specific decompositions. 5-year and 10-year Treasury yields moved in opposite directions throughout the afternoon, so any decomposition of those rates treating the dominant shock as QE2 must allow the asset purchase shock to have opposite signed effects on those variables. However, after most asset purchase shocks, those yields move in the same direction. The disparity is likely due to the different securities targeted by the announcements (see e.g., Anderson and Englander (2010) for market reaction to the QE2 announcement). These facts cannot be reconciled with a single, constant decomposition of asset prices into underlying shocks. Consequently, both RSW and Swanson (2021) record the QE2 shock as contractionary.

August 2011 introduced calendar-based guidance, and accordingly the forward guidance shock had significant effects on the 8-quarter ED rate, the 5-year Treasury yield, and the S&P 500. The following meeting in September 2011 announced "Operation Twist", selling shorter-term Treasuries to buy longer-term Treasuries; the asset purchase shock significantly lowered the 10-year Treasury yield, while not significantly changing shorter rates. This dichotomy presents another example of how a single decomposition cannot characterize the relationship between interest rates and asset purchase shocks for all announcements. Calendar-based guidance was extended in January 2012, but this did not significantly impact interest rates.

September 2012 again extended calendar-based guidance, as well as MBS purchases, but the single shock registered on this day is actually a Fed information shock, since rates increased for much of the afternoon along with the S&P 500. Indeed, the September statement paints a more positive picture of the economy than at the preceding meeting. The December 2012 announcement introduced conditional forward guidance and extended Treasury purchases. Again, however, neither of these shocks appears; instead, a Fed information shock raised both rates and the S&P 500, significantly so for the 10-year Treasury. September 2013, following the "Taper Tantrum", announced that the Fed would wait longer still to taper asset purchases, with the asset purchase shock accordingly lowering interest rates. The announcement also appears to have included an expansionary forward guidance shock.

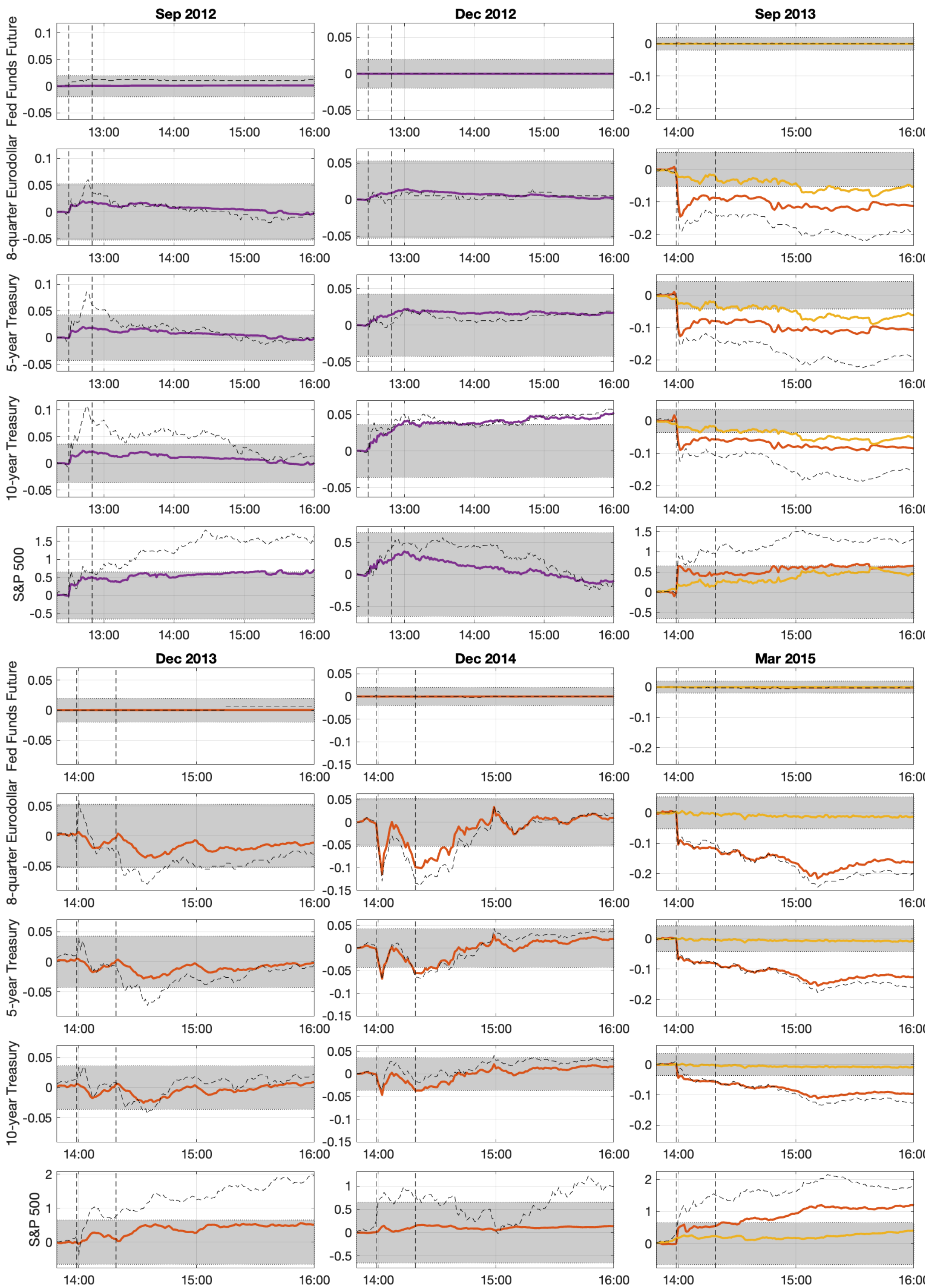
The December 2013 announcement began the tapering of asset purchases, as widely expected, resulting in no asset purchase shock. However, a modification to conditional guidance does seem to have raised the S&P 500. December 2014 introduced language of "patience" with respect to forward guidance, which had only insignificant effects on markets. Finally, March 2015 provided explicit guidance delaying lift-off from the ZLB, and accordingly sparked a significant reduction in all rates and an increase in the S&P 500.

Figure 2: Historical decompositions of key FOMC announcements



Historical decompositions for the rate series indicated in the left margin with respect to each of the four shocks, in percentage points. Blue represents the Fed Funds shock, red the forward guidance shock, gold the asset purchase shock, and purple the Fed information shock. The shaded interval corresponds to 1.96 times the average standard deviation in the asset price following monetary policy announcements. The vertical lines mark the time of the announcement and 20 minutes following the announcement. The black dashed line is the path of the simple change from ten minutes prior to the announcement.

Figure 2b: Historical decompositions of key FOMC announcements (cont'd)



See Figure 2 for notes.

While the bar for significance of these movements in interest rates is admittedly subjective, I characterize the announcements that appear significant based on the measure I adopt. For forward guidance shocks, I focus on the response of 8-quarter ED rates, and for asset purchases I consider both 5- and 10-year Treasury yields. The major forward guidance announcement in March 2009, ("extended period"), the launch of calendar-based guidance in August 2011, and the final March 2015 announcement of an additional FOMC cycle at the ZLB pass the bar. On the asset purchase side, the QE1 announcement of March 2009, Operation Twist in September 2011, and the September 2013 decision to delay tapering led to significant decreases in long-term rates.

For forward guidance, this suggests that the revision of calendar-based guidance, once introduced, did not convey significant new information that markets did not already anticipate in 2012, nor did the switch to conditional guidance change this relationship. Rather, the introduction of explicit forward guidance, and its extension beyond the point where markets expected rates to "lift-off" are two episodes that stand out. The latter accords with the finding of Akkaya et al. (2015) that the potency of forward guidance grows as the distance of the shadow rate from zero shrinks. With respect to the limited effects of changes in forward guidance, Coenen et al. (2017) (in a cross-country study) find that differential effects of different types of forward guidance disappear after omitting observations confounded by simultaneous asset purchase policies.

For asset purchases, the interest rates affected vary across announcements as the nature of announcements changes. The full-scale launch of the policy, its continuation (when markets expected tapering), as well as announcements signaling a change in the focus of purchases, are among the most impactful moves by the FOMC.

These results also illuminate heterogeneity in the response of stocks to monetary policy shocks. Some significant policy shocks do not significantly impact equities (e.g., September 2011 and September 2013 asset purchase shocks) while some shocks with no significant impact on interest rates do significantly affect equity prices, like the December 2008 asset purchase shock or January 2012 forward guidance shock. These latter examples suggest that equity markets may be more sensitive than interest rates to largely priced-in or subtle policy revisions, which is consistent with the finding of Kroencke et al. (2021) that an additional "risk shift" shock is needed to explain variation in stock prices when using a standard time-invariant GSS decomposition. This heterogeneity demonstrates a strength of announcement-specific decompositions, as well as a downside of using interest rate movements alone (as in RSW and Swanson (2021)) to study unconventional monetary policy shocks.

Cieslak and Schrimpf (2019) also analyze the minute-by-minute comovement of yields and stocks over a wide window to characterize monetary policy announcements. They label each announcement's news as conventional policy, unconventional policy, information, or risk premia based on sign restrictions similar to those I use for labeling. Their goal is to analyze variation in these intraday covariances, rather than construct measures of different policy dimensions. The variation they find in covariances across policies is consistent with my analysis: QE1, especially announcements including forward guidance, had the largest monetary policy effects, with smaller movements around tapering and QE2 and QE3.

Bauer et al. (2021) study the effects of monetary policy uncertainty, and argue that changes in uncertainty around monetary policy shocks can explain why some strongly impact asset prices, while others do not. Lower uncertainty amplifies the effects of shocks. Among the key dates discussed above, the announcements that I find to be associated with significant shocks are precisely those that the authors associate with large falls in monetary policy uncertainty. This suggests that their story of uncertainty explaining which shocks are most impactful is consistent with my results.

The preceding analysis highlights how my methodology merges appealing features of preceding papers into a single approach. In particular, Krishnamurthy and Vissing-Jorgensen (2011) compare the effects of QE1 and QE2 announcement-by-announcement, but do so under the implicit assumption of a single shock dimension, since they examine simple changes in asset prices. Often, the change in an asset price used by such approaches is larger than that caused by any one shock, due both to the presence of multiple contributing shocks and the fact that the prices generally contain idiosyncratic noise not contained in the common component of the data. On the other hand, Swanson (2021) allows for simultaneous guidance and asset purchase shocks during the ZLB period, but assumes constant relationships from one announcement to the next. My results allow for up to four dimensions of monetary policy news, including Fed information shocks, and time-varying effects.

These results also illustrate the relative merit of focusing on end-of-day responses, similar to RSW, relative to the conventional 30-minute window.[9] Not all movements in asset prices significant at the 30-minute window remain significant by market close. For example, the initial effect of the December 2014 forward guidance shock is reversed by the end of the day. It is unlikely that interest rate responses that do not even persist to the close of markets are relevant when studying macroeconomic effects, since there is simply no time for them to be transmitted to the broader economy. Allowing for developments outside the conventional 30-minute window is also essential to account for additional revelation or interpretation during and following press conferences. Historically, considering wider windows (to the end of the day) is considered risky, due to potential contamination by noise from other news sources. However, this concern is mitigated under my approach, since, after taking the first k_s principal components of the underlying data to remove idiosyncratic noise, I also discard

[9]RSW consider a 2-hour window from 15 minutes prior to an announcement to 1 hour and 45 minutes following. For a typical 2:00pm announcement, this 1:45-3:45 window is similar to my 1:50-4:01 window.

one or more identified "noise shocks" for many dates where $k_s > k_{mp}$.

Properties of decompositions in the full sample

In general, the preceding conclusions, based on the 12 key announcement dates, are borne out over the remaining 187 announcements considered. Table 5 in Supplement E.2 presents summary statistics across all 199 announcements in my sample. First, computing simple changes in reference interest rates to measure shocks (a simple event study approach) would be misleading, since these changes are considerably larger, on average, than the decompositions allowing for multiple shocks and removing idiosyncratic noise. Second, they affirm that the horizon at which the effects of the shocks are evaluated matters. On average, the effects are weakly larger by the end of the day, although there is heterogeneity across announcements.

Table 2 computes the average relative effects of the different policy measures (across all 199 announcements). I regress the end-of-day decomposition with respect to each shock on the relevant end-of–day decomposition for a reference price: the front Fed Funds future rate for Fed Funds, the 8-quarter ED rate for forward guidance, the average of 5- and 10-year Treasury yields for asset purchases, and the S&P 500 for Fed information. As expected, contractionary Fed funds shocks raise all yields, with the effect falling with maturity, and lower the S&P 500. Forward guidance has the strongest impact on medium-term yields, with asset purchases most strongly impacting long term yields. Both have a negative effect on the S&P 500: about 5 and 11% respectively for shocks lowering reference rates by 1%. The Fed information effect has a moderate impact on medium and long-term yields, with a shock that raises the S&P 500 by 1% increasing longer yields by 3-5 basis points (bps). The effects of monetary policy on stock prices are of the same order of magnitude, but somewhat larger, than those often found in the literature (e.g., Kuttner (2001); Gürkaynak et al. (2005); Swanson (2021)), likely because my methodology accounts for the Fed information effect.

Table 2: Average relative end-of-day effects

	3-m Treasury	6-m Treasury	2-y Treasury	5-y Treasury	10-y Treasury	S&P 500
ϵ_{FF}	0.61*	0.52***	0.38	0.29	0.05	-5.35
ϵ_{FG}	0.07*	0.13**	0.58***	0.75***	0.52***	-4.77***
ϵ_{AP}	0.07*	0.10	0.32**	0.94***	1.06***	-11.04**
ϵ_{FI}	0.00	0.01*	0.05***	0.05***	0.03***	1

Regressions of the end-of-day decomposition with respect to a given shock on the decomposition of the reference price with respect to the same shock. The reference rates are the 8-quarter ED for forward guidance, the average of 5- and 10-year Treasury yields for asset purchases, and S&P 500 returns for Fed information. Coefficients can be interpreted as the response in percentage points to an expansionary shock that changes the reference price by 1%. The sample spans 199 announcements from 2007-2019. HAC standard errors are calculated following Lazarus et al. (2018). Significant results are starred at the 10%, 5% and, 1% levels.

Evidence of time variation in asset price decompositions

These results also support time-varying relationships between asset prices and shocks, undercutting the traditional assumption of a time-invariant decomposition. Figure 12 in Supplement E.2 plots the end-of-day impact of the asset purchase shock on the 5-year Treasury yield, normalized by the impact on the 10-year Treasury yield, across announcements. The relative impact can move dramatically from one announcement to the next, even taking opposite signs. The opposite signs are largely clustered between August 2009 and October 2012, during QE1 and QE2. These results demonstrate that the character of shocks is not necessarily consistent from one announcement to the next, and neither is their effect, as argued by Faust et al. (2007).

I conduct more formal tests of the stability of relative responses of key asset prices to monetary policy. If the decomposition of asset price movements into monetary policy shocks is constant, then the relative responses of asset prices to the same shock are constant. I conduct rolling-window regressions of the responses of pairs of asset prices to a given shock, and compare the coefficients to those from the homogeneous full-sample regressions, computing confidence intervals for each. Figure 13 in the Supplement plots the results. I find evidence rejecting the stability of relative responses for certain shocks. In particular, there is strong time variation in the relative impacts of the asset purchase shock, with greater responsiveness (relative to the effect on the 10-year Treasury) from late 2015 onwards (roughly, once Operation Twist drops out of the sample). There is also evidence of forward guidance having an increased impact on Treasury yields and equities during the ZLB period (although generally not significant), and of interest rates being more sensitive to Fed information shocks during the worst of the Great Recession from 2008-2013. These results indicate that the assumption of a time invariant decomposition of asset price movements into monetary policy shocks may be tenuous, but the development of a more rigourous test is left for future work.

3.3 Robustness and placebo tests

In this section, I describe robustness of the results for key announcement dates to an alternative identification approach and the results of a placebo test based on days containing important macroeconomic news, but no monetary policy announcement.

Alternative identification of key announcement dates

The baseline empirical approach relies on identification via time-varying volatility, exploiting the variation in the volatility of monetary policy shocks from one minute to the next. By virtue of relying on this particularly high-frequency information, this methodology may be susceptible to noise, despite modeling choices to mitigate it. Thus, I consider an alternative form of identification via heteroskedasticity, based on the average variance of shocks across regimes, not minute-by-minute variation, following Rigobon (2003). I define two variance regimes, the conventional 30-minute event window around the announcement, which should be of highest volatility, and the remainder of the afternoon, which should generally be of lower volatility, even as markets continue to process monetary policy news. With this new approach, I repeat the analysis of my baseline model. For ease of comparison, I take k_s to be the same as under the baseline; note, however, that this regime-based approach generally offers less identifying variation (since it leaves variation within regimes on the table), and the identification test of Lütkepohl et al. (2020) indicates fewer identifiable shocks. Thus, the results may not be reliable as stand-alone findings, but can still serve to corroborate my baseline.

Figure 10 in the Supplement plots the results for the 12 key announcement dates. While there are some minor differences in the paths, the shocks found to be significant in the baseline model have virtually the same profiles under this alternative identification scheme. The one exception is the asset purchase shock associated with the delay of tapering, in September 2013, which now barely misses significance. The December 2012 shock is also interpreted as a forward guidance shock instead of a Fed information shock, but remains far from significant, in any case. These results suggest high-frequency noise has minimal impact on identification in the baseline model, since the key findings are essentially unchanged using this alternative approach, which does not exploit high-frequency variation in shock variances.

Placebo test

My identification approach serves to decode movements in asset prices into monetary policy shocks on announcement days, but it is possible that the shocks it recovers are false positives, possibly reflecting other sources of news or noise. To investigate this possibility, I conduct placebo tests by estimating my baseline model on days with no monetary policy shocks. To make this as stern a test as possible, I select the days with the 10 largest macroeconomic release surprises for advance GDP and ADP employment during my sample, as measured by Bloomberg consensus forecasts. Markets are known to follow these releases closely (e.g., Law et al. (2019)). Thus, these are days with very large macroeconomic news shocks, but no monetary policy shocks. I compute decompositions from 10 minutes prior until 2 hours following, broadly aligned with the most common window for the monetary policy announcements.

Table 6 in Supplement E.2 reports the hypothetical end-of-day responses of the front Fed Funds future to the so-called "Fed Funds" shock, the 8-quarter ED rate to the "forward guidance" shock, the 10-year Treasury yield to the "asset purchase" shock, and the S&P 500 return to the "Fed information" shock. Notably, 8 of the 10 labeled shocks across the 10 days are deemed to be Fed information shocks, the criterion for which is, after all, compatible with macroeconomic news in general. None of the releases spark a shock passing the threshold for economic significance used for monetary policy announcements. The responses to the 2 putative forward guidance shocks round to 0.0 bps. for the 8-quarter ED rate. Figure 11 in the Supplement plots the full historical decompositions for each of these placebo dates. These results show that even the largest non-monetary macroeconomic surprises generally do not generate shocks that masquerade as active dimensions of monetary policy, instead appearing as information shocks. Those that are nevertheless labeled as monetary policy shocks are of negligible size.

4 The effects of unconventional monetary policy

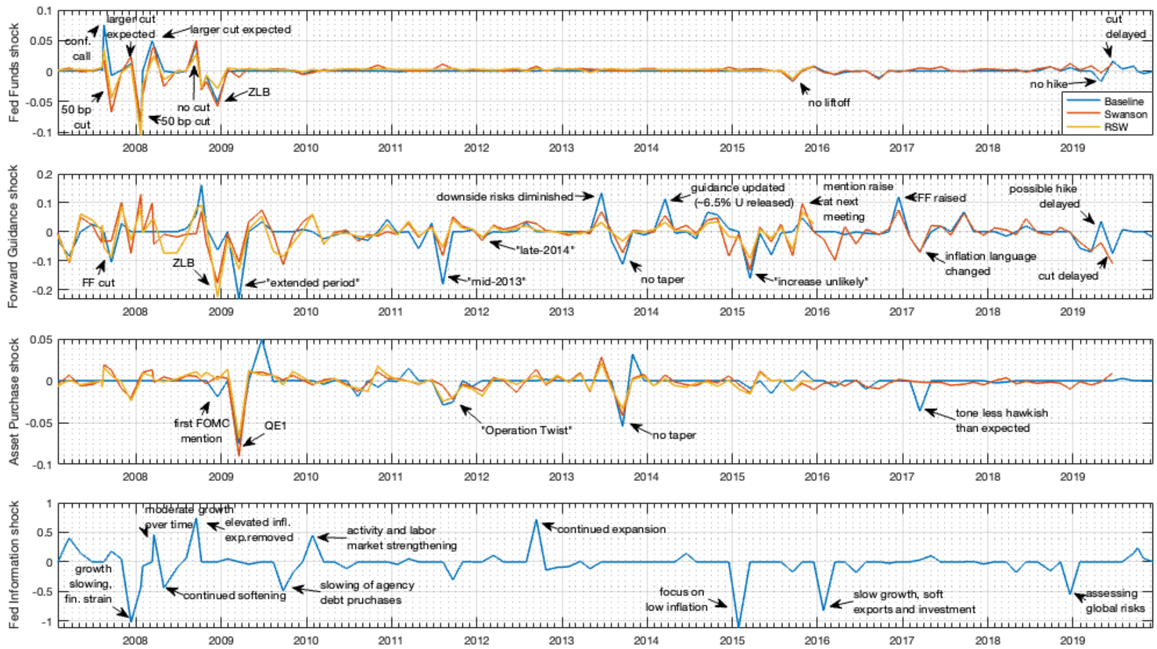
In the previous section, I computed announcement-specific measures of the response of asset prices to monetary policy shocks. My methodology allowed me to consider each date separately. I now conduct more standard analysis of the effects of monetary policy, merging the responses into a timeseries of shocks. I first discuss the properties of the series, compared to leading alternatives. Next, I estimate the effects of the shocks on an array of financial variables. Finally, I estimate the responses of macroeconomic aggregates to my shocks.

4.1 A new monetary policy shock series

While the preceding comparison of the decompositions for notable announcements yields interesting results, many questions can only be answered using an inter-announcement time-series of shocks. To measure the shocks on each day, I use the decomposition at market close for a relevant reference price: the front Fed Funds future rate for Fed Funds, the 8-quarter ED rate for forward guidance, the average of the 5- and 10-year Treasury yields for asset purchases, and the S&P 500 return for Fed information. As explained above, this choice of window helps to capture responses likely to have economic effects, and for most dates is very close or equivalent to that of RSW and Cieslak and Schrimpf (2019). These values form a timeseries of 199 announcement dates. Over this sample, I recover 60 Fed Funds, 109 forward guidance, 29 asset purchase, and 72 Fed information shocks.

Figure 3 plots the timeseries from 2007 until the end of the sample to focus on the period of greatest interest for unconventional policy, annotated with important events. For comparison, I plot the shock series of RSW and Swanson (2021). The behaviour of the new shocks accords with a narrative account. There are large realizations for the Fed Funds shock prior to the ZLB, and then minimal movement until just before lift-off in December 2015. Subsequent movements appear to have been well telegraphed. The largest forward guidance and asset purchase shocks generally correspond to the most notable episodes. The most prominent Fed Information shocks also align with key statements about the state of the economy. Examining the full time series of information shock shows little variation before 2000 and from 2003-2007, consistent with Lunsford (2020), who finds "Delphic" effects during 2000-2003 period, but not from 2003-2006.

Figure 3: Time-series of shock measures



Timeseries of the monetary policy shocks based on end-of-day historical decompositions of reference prices (blue), Swanson (2021) monetary policy shocks (red), and RSW shocks (gold). Units are percentage points of the reference series. Large fluctuations that correspond to notable announcements or statement features are labeled.

Broadly speaking, the shock series are similar to those estimated by Swanson (2021) and RSW. Figures 14 and 15 in the Supplement further explore the time series properties of the shocks, characterizing their autocorrelation functions and their dynamic effects on various Treasury yields, on which basis the measures all appear qualitatively similar. Considering the narrative properties, for the Fed Funds shock, the Swanson and RSW series register some rate cuts in 2007 and 2008 as larger shocks. For forward guidance, the Swanson and RSW series notably allocate most of the first key announcement, in March 2009, to asset purchases instead; Swanson records his largest guidance shock of this period (and third largest overall) two meetings earlier, December 2008, which I find to be well-characterized as a Fed Funds shock. One of his largest forward guidance shocks is associated with the announcement of a 1-quarter extension of QE1 (September 2009); there is no guidance shock on that date in my series. RSW register large shocks in April, June, and September 2008 missing from both other series; the latter appears to be one I identify as a Fed information shock. The series agree on a substantial forward guidance shock with the introduction of calendar guidance (August 2011). However, my series does not register the others' puzzling contractionary shock at the next meeting, which was dominated by Operation Twist. This is likely a distortion due to the fact that time-invariant decompositions cannot reconcile Treasury yields moving in opposite directions for this asset purchase shock. The series agree on a contractionary shock with updated guidance following unemployment reaching 6.5% in March 2014, with similar shocks at subsequent meetings. Finally, the "increase unlikely" shock in May 2015 appears across series.

Turning to asset purchases, my series is zero by construction until December 2008, when the first FOMC statement to mention asset purchases was issued. Because the other series use a constant decomposition over time, they find non-zero shocks (some sizeable) during this period. All three series agree that the March 2009 QE1 announcement was the most significant. The November 2010 QE2 announcement registers as contractionary for both Swanson and RSW, while expansionary for my shocks, as discussed in detail in the preceding section. Operation Twist is also notable across series. Swanson and RSW pick up a large contractionary "taper tantrum" shock in June 2013, puzzling since Bernanke's testimony that provoked the tantrum occurred on May 22nd. If anything, the June 19th announcement should have provided final, *expansionary* confirmation of no taper. My series has no such shock. Finally, the series agree on an expansionary shock with the announcement that there would be no immediate taper in September 2013. While the series are largely similar, there are several key differences for historically important episodes.

4.2 Daily responses of financial variables

I now use my shock series to estimate the effects of monetary policy on financial variables not included in my intraday panel. Event study regressions take the form

$$\Delta r_d = \nu + \psi \epsilon_d^{HF} + u_d, \ d = 1, \dots, D, \tag{8}$$

where d indexes announcement dates, Δr_d is the first difference in the asset price, and ϵ_d^{HF} is the vector of shocks described in Section 4.1, with HAC standard errors.

Table 3 reports the results for the full sample, with results for the ZLB period in Supplement E.5. A contractionary Fed Funds shock has no significant effect on bond yields and spreads, but does cause an appreciation of the dollar against the Yen. During the ZLB sample, there are significant effects on yields and the TIPS spread, but these results must be treated with caution given the extremely small sample of Fed Funds shocks during the period. The forward guidance shock significantly raises yields and lowers spreads on corporate debt and raises the VIX. The same is true during the ZLB subsample, with the TIPS spread also falling and the dollar appreciating against the Yen. Turning to asset purchases, there is a significant increase in corporate yields and a decrease in corporate spreads. In the ZLB subsample, the effects are similar. The Fed information shock increases corporate yields and lowers spreads and reduces the VIX. During the ZLB subsample, there is also an increase in

Table 3: Financial market responses to monetary policy

	AAA yield	AAA spread	Baa yield	Baa spread	TIPS spread	JPY/ USD	Euro/ USD	VIX
FF	0.06	0.14	0.01	0.08	-0.11	5.57**	0.74	-7.47
FG	0.42***	-0.36***	0.40***	-0.38***	-0.19	-1.61	-0.40	61.08***
AP	1.02***	-1.35***	1.31***	-1.06**	-0.39	8.04	4.64	-60.31
FI	0.03	-0.03**	0.05**	-0.02	0.02	-0.32*	0.04	-11.17***

Coefficients are estimated following equation (8) . Coefficients can be interpreted as the response in percentage points to an expansionary shock that changes the reference price by 1%. The sample spans 1996-2019. HAC standard errors are calculated following Lazarus et al. (2018). Significant results are starred at the 10%, 5% and, 1% levels.

the TIPS spread, and the effect on spreads becomes insignificant. While not reported in the table for brevity, I also estimate the effects of the shocks on MBS option-adjusted spreads. In general, the coefficients for the spreads are insignificant, suggesting that the underlying MBS rates rise with Treasury yields (discussed above).

These results largely accord with the existing literature. Swanson (2021) similarly finds limited effects of Fed Funds shocks on corporate bonds, with significant effects on exchange rates. He further observes that (contractionary shocks to) asset purchases significantly raise corporate yields and lower spreads. Additionally, he estimates a negative effect of (contractionary) forward guidance on corporate spreads; however, he recovers an insignificant relationship between forward guidance and corporate yields, in contrast to my result. This response of corporate yields to forward guidance matches results for the "path factor" in Campbell et al. (2012); that of yields to asset purchases aligns with Krishnamurthy and Vissing-Jorgensen (2011). The finding that the response of corporate spreads to asset purchases is positive at longer horizons matches the evidence for conventional policy in Gertler and Karadi (2015). Finally, the finding that forward guidance causes the dollar to appreciate in the ZLB sample is consistent with Swanson (2021) and Rogers et al. (2018). Examining further subsamples, I also observe support for the finding of Paul (2020) that the effect of Fed Funds shocks on stock prices fell in the years preceding the Great Recession. Finally, the finding that contractionary shocks to forward guidance raise the VIX uncertainty measure mirrors results in Coenen et al. (2017).

4.3 Low-frequency effects on the macroeconomy

While financial series are available at high frequency, the macroeconomic aggregates of ultimate importance to central banks are only available at lower frequencies. As a result, little previous work has examined the real effects of unconventional policy shocks in a unified manner. Indeed, neither Swanson (2021) nor RSW examine the response of non-financial variables. In this section, I compute the dynamic responses of key macroeconomic variables to unconventional policy shocks.

I focus my analysis on PCE inflation, unemployment, and industrial production growth. To this point, relatively little work has assessed these impacts, with Baumeister and Benati (2013), Gambacorta et al. (2014), Lloyd (2018), and Inoue and Rossi (2020) being notable exceptions. However, as discussed in the introduction, none of these papers has separated and simultaneously identified interpretable forward guidance and asset purchase shocks.

I aggregate my announcement-frequency shock measures to a monthly timeseries, yielding 288 observations, indexed by r. For a dependent variable, x, I compute impulse response functions using local projections of the form

$$x_{r+h} - x_{r-1} = \alpha^h + \pi_0^h \epsilon_r^{HF} + \sum_{l=1}^{3} \pi_l^h \epsilon_{r-l}^{HF} + \sum_{s=1}^{3} \kappa^h \Delta X_{r-s} + u_r^h, h = 0, 1, \ldots, 12, \tag{9}$$

controlling for the previous quarter's values of monetary policy shocks and monthly macroeconomic aggregates in ΔX_{r-s} (inflation, changes in unemployment, industrial production growth, and S&P 500 returns).[10,11] I consider two sample periods: the full sample, 1996-2019, and a Great Recession (and recovery) sample, 2008-2017.[12] The parameter of interest is the vector π_0^h, the effects of month r shocks at $r + h$. I estimate horizons up to two years, and compute HAC standard errors. I assume constant parameters (e.g., π_0^h), as does virtually the entire extant literature; doing so is necessary due the exercise and sample length. However, my shocks, ϵ_r^{HF}, were recovered without imposing similar assumptions.

[10] I estimate "reduced form" projections as opposed to LP-IV for two reasons. First, IV is generally preferred to a reduced-form regression to achieve an appropriate scaling of the coefficient(s) and address measurement error. However, the process of constructing my shocks already achieves both of these goals, since the shock series measures the impact of the raw minute-by-minute shocks on the asset prices of interest that would form the endogenous regressors. The computation of historical decompositions from the intraday shocks plays the role of a first-stage regression, scaling the shock measures to the relevant asset prices and computing "predicted values", without imposing constant first-stage parameters. Moreover, the effects of a set of several policies, like those I wish to estimate, cannot be simultaneously estimated from a single IV regression without additional assumptions, since the instrumented values in the second stage will be linear combinations of all four shocks, see recent discussions in Mertens and Ravn (2013), Mertens and Montiel Olea (2018), and Arias et al. (2021). While the shock series of RSW and Swanson do not have the same pre-scaled "predicted value" interpretation as mine, IV implementations using those series would still need to confront this challenge, meaning they could not be directly compared to my estimates.

[11] I include the S&P 500 as a control since it has been shown that high-frequency measures of monetary policy shocks are typically not unconditionally orthogonal to lagged information (see., e.g., Barakchian and Crowe (2013); Ramey (2016); Cieslak (2018); Miranda-Agrippino and Ricco (2021)), and S&P 500 returns are a parsimonious proxy for market expectations of future economic outcomes.

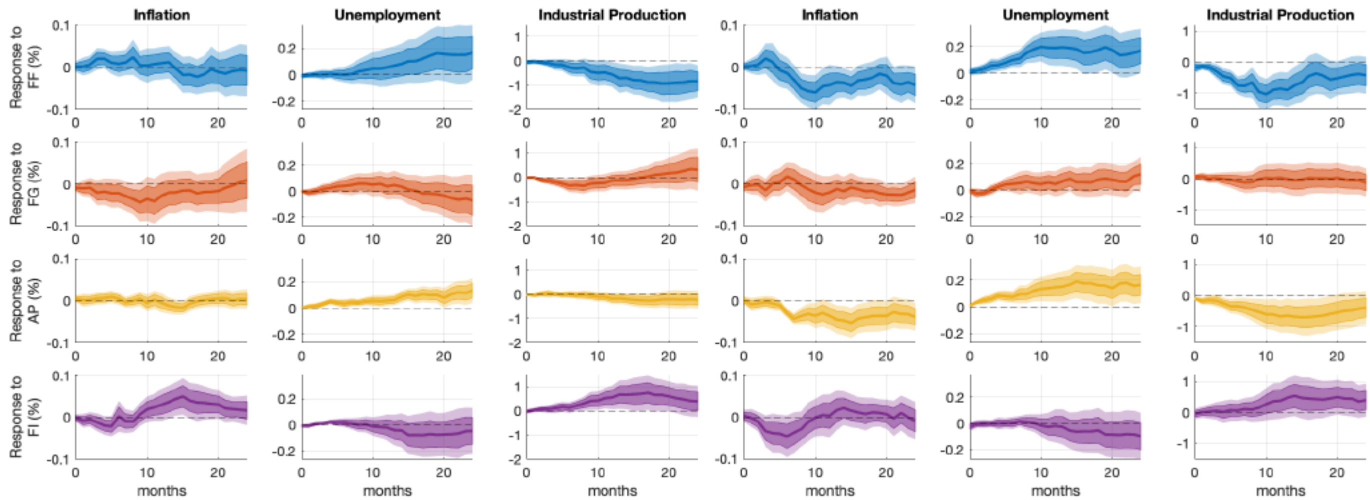
[12] The effective full sample starts in April 1996 (due to lags) and both effective samples end in February 2017 (for the longest horizon) in order to omit pandemic data.

Figure 4 plots the dynamic responses of inflation, unemployment, and industrial production to a one standard deviation contractionary impulse to each shock, with 68% and 90% confidence intervals. For the full sample period, all shocks have essentially the expected effects on each variable. The Fed Funds shock does not have a significant effect on inflation, with a delayed decline, consistent with the price puzzle, but significantly increases unemployment (up to 17 bp) and decreases industrial production (IP, up to -94 bp). The forward guidance shock significantly decreases inflation and IP and raises unemployment within the first year, with effects peaking at -4, -33, and 6 bps, respectively. The asset purchase shock has little effect on inflation, but significantly and persistently increases unemployment and decreases industrial production, 10 and -26 bps, respectively. The Fed information shock (signaling positive news) is associated with higher inflation, lower unemployment, and higher IP (significant except for unemployment), particularly at longer horizons, peaking at -5, 8, and -75 bps, respectively, mirroring findings in Jarociński and Karadi (2020). These results suggest that, in general, conventional policy has larger effects than unconventional policy, while the Fed information shock contains relevant information about the path of the economy.

Turning to the the Great Recession sample, the Fed Funds shock still has significant effects, reducing inflation and IP by up to 6 and 95 bps, respectively, and increasing unemployment by up to 20 bps. These strong responses are the result of a small number of substantial shocks either side of the ZLB, so must be treated with caution. Turning to forward guidance, the results are attenuated relative to the full sample. There are at best marginally significant effects on inflation and unemployment peaking at -3 and 12 bps, and essentially no effect on IP. The story is different for the asset purchase shock, which was not active outside of this subsample. There are highly significant effects on all three variables, peaking at -5, 19, and -70 bps, respectively. There is greater uncertainty around the effects of the Fed Information shock. The increase in inflation after a year is no longer significant, while there is now a significant decrease during the first year. Effects peak at -5, -9, and 53 bps, respectively. The reduced efficacy of forward guidance does not appear to stem from a dearth of shocks or a limited sample, since Figure 3 displays far more notable guidance shocks than asset purchase shocks during this period. The comparatively greater efficacy of asset purchases during this period is supported by recent theoretical work: Sims and Wu (2021) find that asset purchases are considerably more effective than forward guidance, while Hagedorn et al. (2019) find the effects of forward guidance to be negligible.

Figure 4: Dynamic response of macroeconomic aggregates

(a) Full-sample (b) Great Recession



Impulse responses are calculated via local projection as in equation (9) using monthly data. The left panel considers the full sample, effectively January 1996 to December 2019, and the right panel uses a Great Recession sample, January 2008 to December 2017. Responses are scaled to a one standard deviation expansionary impulse. 68% and 90% HAC confidence intervals are calculated following Lazarus et al. (2018).

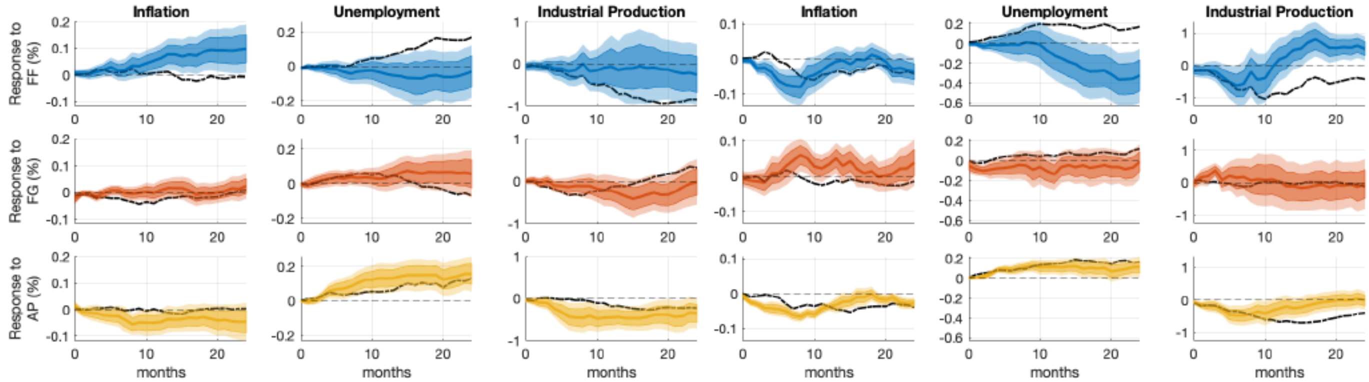
To explore the importance of the Fed information effect, which has recently been challenged by Bauer and Swanson (2022) for example, I estimate an alternative shock series where the S&P 500 is omitted from the panel of asset prices used to estimate the intraday shocks and the maximal dimension of monetary policy is 3, with no Fed information effect. Impulse responses to these alternative shocks are reported in Supplement E.6. Without accounting for the Fed information effect, the signs of the response to Fed Funds shocks flips for both samples. The sign also flips for forward guidance during the main sample, with responses during the Great Recession essentially zero. The effects of asset purchases retain the expected sign. These findings are consistent with results like those in Campbell et al. (2012), Nakamura and Steinsson (2018), and Lunsford (2020), which motivate the identification of a Fed information shock in Jarociński and Karadi (2020) and the present paper. Figures 17 information effects in greater detail. I show that in the model without such shocks, the impacts of monetary policy shocks on equities often have signs consistent with “Delphic” effects, and that effects on the S&P 500 are attenuated, relative to the baseline model. Additionally, the ability of monetary policy shocks to explain equity movements, regardless of sign, is greatly diminished in the model that does not account for information effects.

I have proposed an econometrically relatively complicated approach to recovering monetary policy shocks, so it is natural to ask how the ultimate estimates compare to existing approaches. I first use the RSW shock, which recursively residualizes wide-window changes in the front Fed Funds future rate, the 4-quarter ED rate, and 10-year Treasury yield to recover Fed Funds, forward guidance, and asset purchase shocks, respectively. The top panels of Figure 5 plot responses to these shocks, with the black dash-dot line my baseline responses; each sample ends in 2015, dictated by the availability of the shock series. The results for the Fed Funds shock and forward guidance are very different. During normal times, a contractionary Fed Funds shock *increases* inflation and *decreases* unemployment and negligibly effects IP. During the Great Recession, the effects are slightly more standard, with cuts in inflation and IP at short horizons, although unemployment still puzzlingly falls. In the full sample, forward guidance has little effect on inflation, but does raise unemployment and reduce IP. However, during the Great Recession, it puzzlingly appears to have a small positive effect on inflation and a small negative effect on unemployment – the opposite of what theory predicts. On the other hand, the effects of the RSW asset purchase shock are more similar to those using my shocks, with even larger effects during the full sample and comparable effects during the Great Recession. As discussed previously, the time series properties of the RSW shocks are comparable to those of my baseline series. The fact that the RSW series ends in 2015 plays little role, since the results using my shock series are largely unchanged when the same sample is used. However, the RSW impulse responses are quite similar to those for my alternative shock series identified assuming no information effect, Figure 17 in the Supplement, where I also find paradoxically-signed effects of the Fed Funds shock in particular. This comparison suggests that allowing for an information effect may be important in recovering true "Odyssean" monetary policy shocks. Additionally, Krishnamurthy and Vissing-Jorgensen (2011) highlight the signaling channel through which asset purchases impact expectations of future short rates, but this identification approach assumes that all movements in such expectations (orthogonal to the Fed Funds shock) are forward guidance. Since asset purchases appear more expansionary, while forward guidance appears contractionary, these results suggest that doing so may allocate some variation in rates associated with worsening conditions to forward guidance, instead of to asset purchases.

I next consider the Swanson (2021) shocks, bottom panels of Figure 5. Broadly speaking, the results are much more similar to my baseline results in the full sample. In the full sample, the signs are the same, except that there is a significant price puzzle for the Fed Funds shock, and its impact on unemployment is considerably smaller. The responses of unemployment and IP to forward guidance are more persistent. The effects of asset purchases are considerably larger, -4, 16, and -79 bps, respectively. During the Great Recession, the effects of the Fed Funds shock are more muted and less precisely estimated than for my shock series. The effects of forward guidance are very similar to my baseline, but less precisely estimated, rendering them insignificant. Finally, the effects of asset purchases are quite close

Figure 5: Dynamic response of macroeconomic aggregates: Rogers et al. (2018) shocks

(a) Full-sample (b) Great Recession



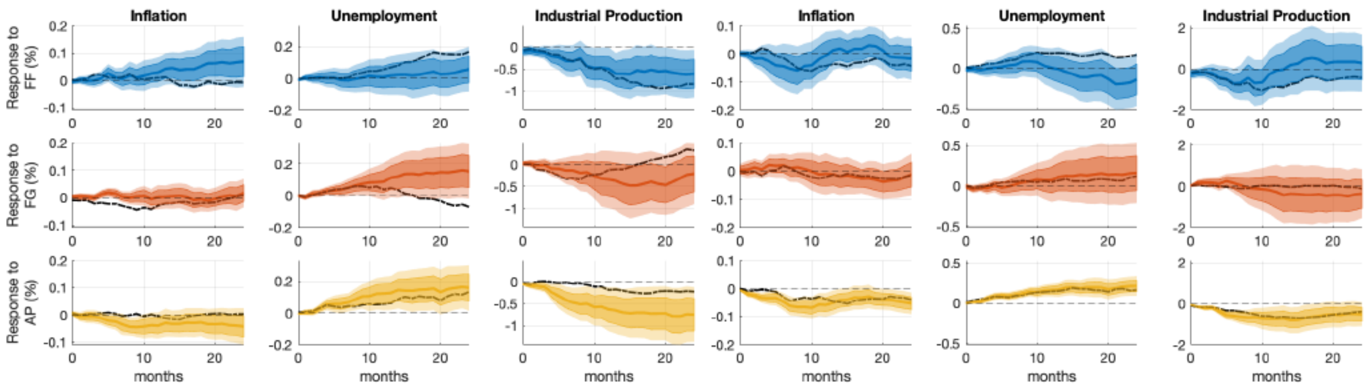
Impulse responses are calculated via local projection as in equation (9) using monthly data and shocks computed using the methodology of Rogers et al. (2018) and their replication data. The left panel considers the full sample, effectively January 1996 to December 2019, and the right panel uses a Great Recession sample, January 2008 to December 2017. Responses are scaled to a one standard deviation expansionary impulse. 68% and 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

for inflation and nearly identical for unemployment and IP. While Swanson does not allow for an information effect, which I argue above presents a problem for the RSW shocks, his use of a 30-minute window instead of the "wide" (2-hour) window of RSW may render the omission less impactful.

There are four important differences between the Swanson shock series and mine. He uses 30-minute windows, while I consider decompositions through market close; I add a fourth shock, a Fed information effect; he assumes a constant decomposition between asset prices and shocks for each event window, while I estimate a unique decomposition between intraday movements; he uses exclusion and narrative restrictions to identify shocks, while I exploit their time varying volatility. Despite these differences, the IRFs obtained are remarkably similar, and lead to the same qualitative conclusions, and in some cases nearly quantitatively equivalent conclusions as well. This constitutes encouraging evidence that my headline results are robust: during normal times, changes to the target rate and forward guidance are effective policy measures, but during the Great Recession, asset purchases became more effective than forward guidance. My results provide further texture by estimating the effects of Fed information shocks, which align with theory. RSW take a much simpler approach, computing a simple Cholesky decomposition of three asset prices to recover their trio of shocks. The agreement between my methodology and Swanson's – and the fact that both produce similar results well-aligned with theoretical predictions – validates the importance of using richer data as well as additional statistical and economic information to identify

Figure 6: Dynamic response of macroeconomic aggregates: Swanson (2021) shocks

(a) Full-sample (b) Great Recession



Impulse responses are calculated via local projection as in equation (9) using monthly data and the Swanson (2021) shocks. The left panel considers the full sample, effectively January 1996 to December 2019, and the right panel uses a Great Recession sample, January 2008 to December 2017. Responses are scaled to a one standard deviation expansionary impulse. 68% and 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

monetary policy shocks, as in these two approaches.

The preceding analysis relates my findings to hypothetical results using existing shocks, but it remains to compare my results to those actually obtained in the literature. Inoue and Rossi (2020) do not report mean responses for the "unconventional" period, instead plotting responses for selected announcements. They break down the overall effects of monetary policy as responses to slope and curvature shocks identified using Nelson and Siegel (1987) loadings. For both output and inflation, they find that the slope factor drives responses, except in 2012, when the influence of the curvature factor increases. The authors argue that the curvature factor can be seen as a forward guidance shock. These findings do not align with my results, which indicate that the forward guidance has had pronounced economic effects for some time, if anything having smaller effects during the Great Recession sample. It is difficult to compare the results further, since their statistically-identified factors do not have clear economic interpretations along the lines of the four dimensions of monetary policy I consider.

Gambacorta et al. (2014) focus on identifying the effects of balance sheet shocks in a cross-country panel VAR. Their findings indicate significant stimulatory effects for asset purchases, peaking around six months. The output response is about three times that of inflation, according with my finding of a much larger response of industrial production.

Bundick and Smith (2020) find moderate effects of forward guidance on output, inflation, and investment. They identify forward guidance shocks extending the path factor of GSS, but do not control for coincident asset purchases in their baseline analysis, although their results are fairly robust to dropping key LSAP dates. This is consistent with my finding that forward guidance is in general effective, but less so during the Great Recession.

Finally, Gertler and Karadi (2015) find suggestive evidence that forward guidance serves to amplify shocks to the current policy rate. They do so by comparing responses using the front Fed Funds future as an instrument for the Fed Funds rate to their baseline, which uses three-month ahead futures to instrument for the 1-year Treasury yield. However, their sample runs from 1991-2012, so is dominated by observations outside of the ZLB. Thus, their evidence that forward guidance can offer additional stimulus may be compatible with my finding that it had only a modest impact during the Great Recession. Indeed, since they argue that forward guidance may be effective by *augmenting* policy rate shocks, the discrepancy accords with the fact that the Fed Funds rate was at the ZLB, so policy rate shocks were not forthcoming.

Previous work has additionally examined the effect of unconventional policy shocks on the expectations of professional forecasters (e.g., Campbell et al. (2012); Nakamura and Steinsson (2018)); the expectations channel is theoretically important to the transmission of unconventional monetary policy (see e.g., Eggertsson and Woodford (2003); McKay et al. (2016)). A companion paper, Lewis et al. (2019), conducts similar analysis, focused instead on consumer sentiment. My results also offer some early evidence of whether the effects that Campbell et al. (2012) and Nakamura and Steinsson (2018) find for Fed information shocks on forecasts extends to real activity. I find that the Fed information shock has a significant positive effect on industrial production, an insignificant but pronounced negative effect on unemployment, and a positive and significant effect on inflation at longer horizons in the full sample.

5 Conclusion

I use intraday data on asset prices to recover high frequency timeseries of monetary policy shocks on announcement days using announcement-specific decompositions. This flexible approach to identifying the effects of news shocks could be adapted to many other contexts, including macroeconomic releases or corporate news. I identify the decompositions based on time-varying volatility. I recover four dimensions of monetary policy shocks: Fed Funds, forward guidance, asset purchase, and Fed information. Because I am able to identify different decompositions for each announcement, I can compare the effects of shocks directly from one announcement to the next. Focusing on the Great Recession period, I find that a small handful of notable FOMC announcements of unconventional measures sparked significant monetary policy shocks. In particular, the leading announcements are the strengthening of forward guidance (March 2009), the introduction of calendar-based guidance (August 2011), forward guidance prolonging the ZLB (March 2015), the dramatic expansion of QE1 (March 2009), Operation Twist (September 2011), and the decision to delay tapering (September 2013). The fact that these announcements are dominated by the launch of new policies or unexpected extension of existing policies indicates that the utilization of these tools, as opposed to more subtle adjustments of policies or statement language, is what matters to markets. I also find that conclusions based on simple event-studies or standard 30-minute changes in asset prices may be unreliable, on some days overstating effects, and on some days understating them.

Contractionary forward guidance and asset purchase shocks raise corporate yields, lower spreads, and raise uncertainty, while forward guidance also raised the TIPS spread and appreciated the dollar against the Yen during the ZLB period. Fed information shocks raise yields and lower uncertainty. Most importantly, I find substantial macroeconomic effects. In the full sample, inflation, unemployment, and industrial production display significant dynamic responses to Fed Funds, forward guidance, and asset purchase shocks, but during the Great Recession, the effects of asset purchases are much more pronounced than those of forward guidance. I obtain similar results using the Swanson (2021) shocks, supporting the robustness of these findings. However, using the simpler RSW measures leads to very different impulse responses with puzzling signs. Taken together, these results offer novel evidence on the macroeconomic effects of the Federal Reserve's unconventional monetary policy, stratified by policy dimension, while controlling for information effects. They suggest that both forward guidance and asset purchase policies have been effective with regard to a number of macroeconomic outcomes, with the latter proving more effective during the Great Recession. I additionally offer novel support for the Fed information effect, finding it is crucial to explaining the movement of stock returns on announcement days and ensuring that macroeconomic responses represent "Odyssean" effects.

References

Aït-Sahalia, Y. and J. Yu (2009): "High frequency market microstructure noise estimates and liquidity measures," *Annals of Applied Statistics*, 3, 422–457.

Akkaya, Y., R. S. Gürkaynak, B. Kisackoğlu, and J. H. Wright (2015): "Forward Guidance and Asset Prices," *IMES Discussion Paper Series*.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2003): "Modeling and Forecasting Realized Volatility," *Econometrica*, 71, 579–625.

Anderson, G. and S. Englander (2010): "FX Alert - FOMC meets expectations as 'mandated'," CitiFX and LM Strategy Market Commentary.

Arias, J. E., J. F. Rubio-Ramírez, and D. F. Waggoner (2021): "Inference in Bayesian Proxy-SVARs," *Journal of Econometrics*, 225, 88–106, themed Issue: Vector Autoregressions.

Bai, J. and S. Ng (2002): "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70, 191–221.

Barakchian, S. M. and C. Crowe (2013): "Monetary policy matters: Evidence from new shocks data," *Journal of Monetary Economics*, 60, 950–966.

Barndorff-Nielsen, O. E. and N. Shephard (2002): "Econometric Analysis of Realized Volatility and Its Use in Estimating Stochastic Volatility Models," *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 64, 253–280.

Bauer, M. D., A. Lakdawala, and P. Mueller (2021): "Market-Based Monetary Policy Uncertainty," *The Economic Journal*, 132, 1290–1308.

Bauer, M. D. and E. T. Swanson (2022): "An Alternative Explanation for the "Fed Information Effect"," *NBER Working Paper 27013*.

Baumeister, C. and L. Benati (2013): "Unconventional Monetary Policy and the Great Recession: Estimating the Macroeconomic Effects of a Spread Compression at the Zero Lower Bound," *International Journal of Central Banking*, 9, 165–212.

Brockwell, P., E. Chadraa, and A. Lindner (2006): "Continuous-time GARCH processes," *The Annals of Applied Probability*, 16, 790 – 826.

Bundick, B. and A. L. Smith (2020): "The Dynamic Effects of Forward Guidance Shocks," *The Review of Economics and Statistics*, 102, 946–965.

Campbell, J. R., C. L. Evans, J. D. Fisher, and A. Justiniano (2012): "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 80, 1–80.

Campbell, J. Y., A. W. Lo, and A. C. MacKinlay (1997): *The Econometrics of Finance*, Princeton, NJ: Princeton University Press.

Cieslak, A. (2018): "Short-Rate Expectations and Unexpected Returns in Treasury Bonds," *The Review of Financial Studies*, 31, 3265–3306.

Cieslak, A. and A. Schrimpf (2019): "Non-monetary news in central bank communication," *Journal of International Economics*, 118, 293–315.

Coenen, G., M. Ehrmann, G. Gaballo, P. Hoffmann, A. Nakov, S. Nardelli, E. Persson, and G. Strasser (2017): "Communication of Monetary Policy in Unconventional Times," *CFS Working Paper Series*.

Eggertsson, G. and M. Woodford (2003): "The Zero Bound on Interest Rates and Optimal Monetary Policy," *Brookings Papers on Economic Activity*, 34, 139–235.

Faust, J., J. Rogers, S. Wang, and J. Wright (2007): "The high-frequency response of exchange rates and interest rates to macroeconomic announcements," *Journal of Monetary Economics*, 54, 1051–1068.

Gambacorta, L., B. Hofmann, and G. Peersman (2014): "Unconventional Monetary Policy at the Zero Lower Bound : A Cross-country Analysis," *Journal of Money, Credit and Banking*, 46, 615–642.

Gertler, M. and P. Karadi (2015): "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics*, 7, 44–76.

Gürkaynak, R. S., B. Kisacikoğlu, and J. H. Wright (2020): "Missing Events in Event Studies: Identifying the Effects of Partially Measured News Surprises," *American*

Economic Review, 110, 3871–3912.

Gürkaynak, R. S., B. Sack, and E. T. 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.

Hagedorn, M., J. Luo, I. Manovskii, and K. Mitman (2019): "Forward guidance," *Journal of Monetary Economics*, 102, 1–23.

Inoue, A. and B. Rossi (2020): "The Effects of Conventional and Unconventional Monetary Policy: A New Approach," *NBER Working Papers*.

Jarociński, M. (2022): "Estimating the Fed's unconventional policy shocks," *European Central Bank Working Paper Series*.

Jarociński, M. and P. Karadi (2020): "Deconstructing Monetary Policy Surprises?The Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12, 1–43.

Karlin, S. and H. M. Taylor (1975): *A First Course in Stochastic Processes*, San Diego: Elsevier.

Kim, S., N. Shephard, and S. Chib (1998): "Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models," *The Review of Economic Studies*, 65, 361–393.

Krishnamurthy, A. and A. Vissing-Jorgensen (2011): "The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy," *Brookings Papers on Economic Activity*, 2011.

Kroencke, T. A., M. Schmeling, and A. Schrimpf (2021): "The FOMC Risk Shift," *Journal of Monetary Economics*, 120, 21–39.

Kuttner, K. N. (2001): "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of Monetary Economics*, 47, 523–544.

Law, T. H., D. Song, and A. Yaron (2019): "Fearing the Fed: How Wall Street Reads Main Street," *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Lazarus, E., D. J. Lewis, J. H. Stock, and M. W. Watson (2018): "HAR Inference: Recommendations for Practice," *Journal of Business & Economic Statistics*, 36, 541–559.

Lewis, D. J. (2021): "Identifying Shocks via Time-Varying Volatility," *The Review of Economic Studies*, 88, 3086–3124.

Lewis, D. J., C. Makridis, and K. Mertens (2019): "Do Monetary Policy Announcements Shift Household Expectations?" *Federal Reserve Bank of Dallas Working Papers*.

Lloyd, S. P. (2018): "Unconventional Monetary Policy and the Interest Rate Channel: Signalling and Portfolio Rebalancing," *Cambridge Working Papers in Economics*.

Lunsford, K. G. (2020): "Policy Language and Information Effects in the Early Days of Federal Reserve Forward Guidance," *American Economic Review*, 110, 2899–2934.

Lütkepohl, H., M. Meitz, A. Netšunajev, and P. Saikkonen (2020): "Testing Identification via Heteroskedasticity in Structural Vector Autoregressive Models," *The Econometrics Journal*.

McKay, A., E. Nakamura, and J. Steinsson (2016): "The Power of Forward Guidance Revisited," *American Economic Review*, 106, 3133–3158.

Mertens, K. and J. L. Montiel Olea (2018): "Marginal Tax Rates and Income: New Time Series Evidence," *The Quarterly Journal of Economics*, 133, 1803–1884.

Mertens, K. and M. O. Ravn (2013): "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, 103, 1212–47.

Miranda-Agrippino, S. and G. Ricco (2021): "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, 13, 74–107.

Nakamura, E. and J. Steinsson (2018): "High Frequency Identification of Monetary Non-Neutrality: The Information Effect," *Quarterly Journal of Economics*, 133, 1283–1330.

Nelson, C. R. and A. F. Siegel (1987): "Parsimonious Modeling of Yield Curves," *The Journal of Business*, 60, 473–489.

Paul, P. (2020): "The Time-Varying Effect of Monetary Policy on Asset Prices," *The Review of Economics and Statistics*, 102, 690–704.

Ramey, V. (2016): "Chapter 2 - Macroeconomic Shocks and Their Propagation," Elsevier, vol. 2 of *Handbook of Macroeconomics*, 71–162.

Rigobon, R. (2003): "Identification through Heteroskedasticity," *The Review of Economics and Statistics*, 85, 777–792.

Rigobon, R. and B. Sack (2003): "Measuring the Reaction of Monetary Policy to the Stock Market," *Quarterly Journal of Economics*, 118, 639–669.

——— (2004): "The Impact of Monetary Policy on Asset Prices," *Journal of Monetary Economics*, 51, 1553–1575.

Rogers, J. H., C. Scotti, and J. H. Wright (2018): "Unconventional Monetary Policy and International Risk Premia," *Journal of Money, Credit and Banking*, 50, 1827–1850.

Shephard, N. (1996): "Statistical Aspects of ARCH and Stochastic Volatility," in *Time Series Models: in Econometrics, Finance and Other Fields*, ed. by D. Cox, D. Hinkley, and O. Barndorff-Nielsen, New York: Chapman & Hall, 1–68.

Sims, E. and J. C. Wu (2021): "Evaluating Central Banks' tool kit: Past, present, and future," *Journal of Monetary Economics*, 118, 135–160.

Swanson, E. T. (2021): "Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets," *Journal of Monetary Economics*, 118, 32–53.

A Proof of Proposition 1

Proposition 1. *Under the model described by (4) and (5), H_d^{inf}, infeasibly identified from repeated samples of η_d, is identical to H_d.*

Proof. By definition, it follows that

$$P_t - P_{t-\delta} = \int_0^t \eta(s)\, ds - \int_0^{t-\delta} \eta(s)\, ds = H_d \int_{t-\delta}^t \epsilon(s)\, ds = H_d \epsilon_d.$$

Any valid identification scheme for H_d^{inf} based on moments of $\eta_d \left(= H_d^{inf} \epsilon_d\right)$ (computed from infeasible repeated samples) must necessarily recover a unique linear mapping between η_d and ϵ_d; since H_d provides such a mapping, it must be that $H_d^{inf} = H_d$. □

B Identification results in continuous time

In this section, I derive population moments for returns under the model (4) and (5) as limits of discrete moments, following an infill argument. I then show that simple sample averages of discrete returns converge almost surely to the same moments of the continuous return process. Together, these results show that the moments used for identification (the population continuous time moments) are consistently estimable by simple non-parametric sample averages. To establish consistency, I additionally assume that $\sigma^2(t)$ is ergodic.

B.1 Limiting moments of discrete returns

In a simple generalization from a univariate to multivariate model, it follows from Barndorff-Nielsen and Shephard (2002) that

$$E\left[M\epsilon_m\epsilon_m'\right] = M \times E\left[D\left(\sigma_m^2\right)\right] = M \times D(\xi)/M = D(\xi),$$

where ξ is the $n \times 1$ unconditional mean of $\sigma^2(t)$. It is immediate that $E\left[M\eta_m\eta_m'\right] = H\xi H'$.

Turning to the other moment used in the identification argument,

$$\operatorname{cov}\left(\sigma_m^2, \sigma_{m-pM}^2\right) = \Omega_D^{1/2} \diamondsuit R^{**}(pM \times 1/M)\, \Omega_D^{1/2}$$

where Ω_D is a diagonal matrix containing the diagonal of $\Omega = \operatorname{var}\left(\sigma^2(t)\right)$,

$$\diamondsuit R^{**}(p) = R^{**}(p + 1/M) - 2R^{**}(p) + R^{**}(p - 1/M),$$

and

$$R^*(t) = \int_0^t R(u)\, du \text{ and } R^{**}(t) = \int_0^t R^*(u)\, du,$$

where $R(u)$ is the $n \times n$ autocorrelation function of $\sigma^2(t)$. The use of lag pM ensures a constant time distance, p, even as the distance between observations decreases in M. Using a Taylor expansion of $R^{**}(s+t)$ around s yields

$$R^{**}(s+t) = R^{**}(s) + R^*(s)\, t + \frac{R(s)}{2} t^2 + o\left(t^2\right).$$

Then

$$\begin{aligned}
\diamondsuit R^{**}(p) &= \left(R^{**}(p) + R^{*}(p)\frac{1}{M} + \frac{R(p)}{2}\left(\frac{1}{M}\right)^2\right) - 2R^{**}(p) \\
&\quad + \left(R^{**}(p) - R(p)\frac{1}{M} + \frac{R(p)}{2}\left(\frac{-1}{M}\right)^2\right) + o\left(\left(\frac{1}{M}\right)^2 + \left(\frac{-1}{M}\right)^2\right) \\
&= \frac{R(p)}{2}\frac{2}{M^2} + o\left(1/M^2\right) \\
&= R(p)/M^2 + o\left(1/M^2\right).
\end{aligned}$$

Thus,

$$\text{cov}\left(\sigma_m^2, \sigma_{m-pM}^2\right) = \Omega_D^{1/2} R(0)\, \Omega_D^{1/2}/M^2 + o\left(1/M^2\right),$$

so

$$\text{cov}\left(M\sigma_m^2, M\sigma_{m-pM}^2\right) = \Omega_D^{1/2} R(p)\, \Omega_D^{1/2} + o(1) = \text{cov}\left(\sigma^2(t), \sigma^2(t-p)'\right) + o(1),$$

and

$$\lim_{M\to\infty} \text{cov}\left(M\sigma_m^2, M\sigma_{m-pM}^2\right) = \text{cov}\left(\sigma^2(t), \sigma^2(t-p)'\right).$$

Applying Proposition 1 from Lewis (2021), it is immediate that

$$\lim_{M\to\infty} \text{cov}\left(M\zeta_m, M\zeta_{m-pM}'\right) = L(H\otimes H)\, G\left(\Omega_D^{1/2} R(p)\, \Omega_D^{1/2}\right) G'(H\otimes H)' L',$$

where $\zeta_m = vech\left(\eta_m \eta_m'\right)$ and L and G are elimination and selection matrices of zeros and ones.

A similar approach, instead taking an expansion around $s = 0$, shows that

$$\lim_{M\to\infty} \text{var}\left(M\sigma_m^2\right) = \Omega.$$

B.2 Consistent estimation of continuous time moments

In this section, I show that simple (rescaled) sample averages of equally spaced returns are consistent for the population moments used for identification, as in large$-T$ settings. In particular, it is not necessary to use a stratified approach, first estimating variances using a local average, and then estimating moments of those estimated variances (as in e.g., Barndorff-Nielsen and Shephard (2002)).

A (rescaled) sample average of M $1/M-$spaced squared returns converges almost surely to $HD(\xi)H'$, the mean of $\eta(t)\eta(t)'$. Since $\eta_m = H\epsilon_m$, and H is invertible, it suffices to show that a sample average of $\epsilon_m \epsilon_m'$ converges almost surely to $D(\xi)$. In particular,

$$\frac{1}{M}\sum_{m=1}^{M} M\epsilon_m\epsilon_m' = \frac{1}{M}\sum_{m=1}^{M} MD\left(E\left[\sigma_m^2\right]\right) + \frac{1}{M}\sum_{m=1}^{M} M\left(\epsilon_m\epsilon_m' - D\left(E\left[\sigma_m^2\right]\right)\right)$$
$$= D(\xi) + \frac{1}{M}\sum_{m=1}^{M} M\left(\epsilon_m\epsilon_m' - D\left(E\left[\sigma_m^2\right]\right)\right).$$

The summand in the final expression is mean-zero since it consists of a random variable minus its unconditional expectation. The variance of $M\epsilon_m\epsilon_m'$ is finite as $\lim_{M\to\infty} \text{var}\left(M\sigma_m^2\right) = \Omega$ and, conditional on σ_m^2, ϵ_m is random normal with variance σ_m^2. Since $\sigma^2(t)$ is assumed to be ergodic and increments of Brownian motion are independent, applying the ergodic theorem (e.g., Karlin and Taylor (1975)) to the sample average shows that it converges almost surely to 0. Thus,

$$\frac{1}{M}\sum_{m=1}^{M} M\epsilon_m\epsilon_m' \overset{a.s.}{\to} D(\xi) + 0 = D(\xi).$$

Therefore,

$$\frac{1}{M}\sum_{m=1}^{M} M\eta_m\eta_m' \overset{a.s.}{\to} HD(\xi)H'.$$

Next, noting that $vec(\eta_m\eta_m') = vec(H\epsilon_m\epsilon_m' H') = (H\otimes H)\, vec(\epsilon_m\epsilon_m')$, I show that a sample autocovariance of $\epsilon_m\epsilon_m'$ converges almost surely to the autocovariance of $\sigma^2(t)$ at distance p, $\Omega_D^{1/2} R(p)\,\Omega_D^{1/2}$. Consider the (rescaled) pM sample autocovariance of $vec(\epsilon_m\epsilon_m')$,

$$\frac{1}{M}\sum_{m=pM+1}^{M} M^2 vec(\epsilon_m\epsilon_m')\, vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)' - \left(\frac{1}{M}\sum_{m=1}^{M} M vec(\epsilon_m\epsilon_m')\right)\left(\frac{1}{M}\sum_{m=1}^{M} M vec(\epsilon_m\epsilon_m')\right)'.$$

The sample average in the second term converges almost surely to $vec(diag(\xi))$, so the second term converges to $G\xi\xi' G'$. The first term can be decomposed as

$$\frac{1}{M}\sum_{m=pM+1}^{M} M^2 vec(\epsilon_m\epsilon_m')\, vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)' = \frac{1}{M}\sum_{m=pM+1}^{M} M^2 E\left[vec(\epsilon_m\epsilon_m')\, vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)'\right].$$
$$+ \frac{1}{M}\sum_{m=pM+1}^{M} M^2 \left\{vec(\epsilon_m\epsilon_m')\, vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)'\right.$$
$$\left. - E\left[vec(\epsilon_m\epsilon_m')\, vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)'\right]\right\}$$

The first of these summands can be further decomposed as

$$
\begin{aligned}
& M^2 E\left[vec\left(\epsilon_m\epsilon_m'\right) vec\left(\epsilon_{m-pM}\epsilon_{m-pM}^{'}\right)'\right] \\
& = M^2 G E\left[\sigma_m^2 \sigma_{m-pM}^{2'}\right] G' \odot \left(vec\left(E\left[z_m z_m^{'}\right]\right) vec\left(E\left[z_{m-pM} z_{m-pM}^{'}\right]\right)'\right) \\
& = M^2 G E\left[\sigma_m^2 \sigma_{m-pM}^{2'}\right] G' \odot \left(v_n v_n^{'}\right) \\
& = M^2 G E\left[\sigma_m^2 \sigma_{m-pM}^{2'}\right] G' \\
& = G\mathrm{cov}\left(M\sigma_m^2, M\sigma_{m-pM}^{2'}\right) G' + G\xi\xi' G',
\end{aligned}
$$

where z_j is an $n \times 1$ standard normal random variable and $v_n = vec\left(I_n\right)$. The second summand is mean zero. It follows that it has finite variance since $\sigma^2\left(t\right)$ is assumed to have finite fourth moments and, conditional on σ_m^2, ϵ_m is random normal with variance σ_m^2.[13] Using the ergodicity of $\sigma^2\left(t\right)$ and the independence of increments of Brownian motion, the second sample average converges to zero almost surely. Thus,

$$
\begin{aligned}
& \frac{1}{M}\sum_{m=pM+1}^{M} M^2 vec\left(\epsilon_m\epsilon_m'\right) vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)' \\
& \overset{a.s.}{\to} \lim_{M\to\infty} G\mathrm{cov}\left(M\sigma_m^2, M\sigma_{m-pM}^2\right) G' + G\xi\xi' G' + 0 \\
& = G\Omega_D^{1/2} R\left(p\right) \Omega_D^{1/2} G' + G\xi\xi' G'.
\end{aligned}
$$

Finally,

$$
\begin{aligned}
& \frac{1}{M}\sum_{m=pM+1}^{M} M^2 vec\left(\epsilon_m\epsilon_m'\right) vec\left(\epsilon_{m-pM}\epsilon_{m-pM}'\right)' - \left(\frac{1}{M}\sum_{m=1}^{M} M vec\left(\epsilon_m\epsilon_m'\right)\right)\left(\frac{1}{M}\sum_{m=1}^{M} M vec\left(\epsilon_m\epsilon_m'\right)\right)' \\
& \overset{a.s.}{\to} G\Omega_D^{1/2} R\left(p\right) \Omega_D^{1/2} G' + G\xi\xi' G' - G\xi\xi' G' \\
& = G\Omega_D^{1/2} R\left(p\right) \Omega_D^{1/2} G'.
\end{aligned}
$$

This immediately implies that

$$
\begin{aligned}
& \frac{1}{M}\sum_{m=pM+1}^{M} M^2 \zeta_m \zeta_{m-pM}' - \left(\frac{1}{M}\sum_{m=1}^{M} M\zeta_m\right)\left(\frac{1}{M}\sum_{m=1}^{M}\zeta_m\right)' \\
& \overset{a.s.}{\to} L\left(H\otimes H\right) G\left(\Omega_D^{1/2} R\left(p\right) \Omega_D^{1/2}\right) G'\left(H\otimes H\right)' L',
\end{aligned}
$$

[13]In particular, taking fourth moments of the integral yielding σ_m^2 and recognizing that the entries of $R\left(t\right)$ are bounded by ± 1 delivers the result.

as required.

C Details on augmented historical decompositions

It is straightforward to compute historical decompositions of each asset price, Y_m, to each of the k_s shocks, $\epsilon_{j\cdot}$. In particular, let the impulse response matrix of F_m to ϵ_m at horizon h be ϕ_h. Then the historical decomposition of F_m with respect to $\epsilon_{j\cdot}$ is $\sum_{h=0}^{m} \phi_h \iota_j \epsilon_{m-h}$, where ι_j is the j^{th} column of the $k_s \times k_s$ identity matrix, and the decomposition of the differenced data $\Delta\tilde{Y}_m$ is given by $\Lambda \sum_{h=0}^{m} \phi_h \iota_j \epsilon_{m-h}$. Finally, rescaling by $D(\sigma_{\Delta Y})$, which diagonalizes $\sigma_{\Delta Y}$ (the standard deviation of ΔY_m), and cumulating the decomposition gives the value for the data in levels, Y_m,

$$\Psi_{jm} = \sum_{s=1}^{m} D(\sigma_{\Delta Y}) \Lambda \sum_{h=0}^{s} \phi_h \iota_j \epsilon_{s-h}. \tag{10}$$

However, I work with a modified historical decomposition, $\bar{\Psi}_{jm}$, in order to obtain counterfactual paths that actually sum to the trajectory of the data in levels, Y_m.[14] First differences ΔY_m are standardized to $\Delta\tilde{Y}_m$ before computing principal components. While multiplication by $\sigma_{\Delta Y}$ in (10) undoes the scaling, it is also necessary to undo the demeaning of ΔY_m. When summing across m to compute Ψ_{jm}, cumulating $\Delta\tilde{Y}_m$ responses introduces a mechanical $-\mu m$ "wedge", where μ is the mean of ΔY_m (which was subtracted to compute $\Delta\tilde{Y}_m$), between Ψ_{jm} and Y_m. This wedge implies a mechanical drift towards zero, since $\sum_{m=1}^{M} \Delta\tilde{Y}_m = 0$. Without adjustment, every historical decomposition would pass near zero at M, regardless of the value of Y_M. I thus add a drift term into the decompositions so that, in sum, they match the path of Y_m. It is desirable that adding decompositions across shocks j should sum to the movement in Y_m explained by the first k_s principal components and that shocks on which Y_m places zero weight (through Λ, H, or both) should have a decomposition value of zero. Simply adding μm back in to all $\bar{\Psi}_{jm}$ would violate both of these conditions. Instead, I add a total of μm across all shocks j, adding $w_{ijm}\mu m$ to each decomposition Ψ_{ijm}, where $w_{ijm} = \left|\Psi_{ij(m-1)}\right| / \sum_{l=1}^{k_s} \left|\Psi_{il(m-1)}\right|$. This allocates a portion of the deterministic drift at each 1-minute interval to each shock path commensurate with its role up to that point in explaining the movement of Y_m.

[14] More precisely, I refer to summing to the path of Y_m explained by the first k_s principal components, since the exact path of a given variable, Y_{im}, will not be traced out by the first $k_s \leq 4$ principal components of Y_m, regardless of what transformations are adopted prior to computation.

D Details on shock labeling

Having estimated the k_s identifiable shocks, it remains to label the k_{mp} monetary policy shocks. Recall that the dimensions k_s and k_p are estimated separately first to ensure that there is in fact adequate heteroskedasticity to identify the monetary policy shocks and second to account for the fact that innovations to the common component (the first k_{mp} principal components) may also include the influence of noise shocks (see main text for further discussion). I label k_{mp} of the k_s shocks based on the augmented historical decompositions of the 20 data series with respect to the k_s identifiable shocks. To overview the exercise, suppose that $k_s = k_{mp} = 4$. There are 4 possible labels for each shock, leading to $4! = 24$ possible labelings in total. Suppose instead that $k_{mp} = 3$. There will still be 24 possible labelings, since it remains to determine which label goes unused. In the case of $k_s = 2$, there are 12 possible labelings (no order is assigned to unused labels) and, for $k_s = 1$, there are only 4. Below I describe a quantitative criterion that will separately measure the "economic reasonableness" of each candidate labeling and select the one most aligned with economic theory. The criterion also determines which shocks are discarded when $k_{mp} < k_s$, and also which labels go unused when $k_{mp} < 4$, retaining the k_{mp} shocks that best fit the economic properties of monetary policy shocks, and the labels for which the most appropriate shocks are found, respectively.

Let $A_{ij} = M^{-1} \sum_{m=1}^{M} \Psi_{ijm}$ be the integral of the path traced out by the historical decomposition of series i with respect to shock j, and $\bar{A}_i = M^{-1} \sum_{m=1}^{M} Y_{im}$ the integral of the observed path of series i. I measure the share of movement in series i explained by shock j as

$$\Theta_{ij} = \min\left(A_{ij}/\bar{A}_i, 1\right),$$

bounded above at 1 (which is very rarely a binding condition). I also compute S_{ij}, a measure of the sign of the response of each series to each shock,

$$S_{ij} = Sign\left(\Psi_{ij31} + \Psi_{ijM}\right),$$

considering both the end of the conventional 30-minute event study window as well as the market close. I apply a sequence of rules based on Θ and S to evaluated the economic reasonableness of each shock-label pairing and ultimately label k_{mp} of the k_s shocks.

I define a $4 \times k_s$ matrix-valued criterion function, $C(S, \Theta)$, taking values on $(-\infty, 1]$ for each candidate shock and label as follows. For the Fed Funds shock,

$$C_{FF,j}\left(S_{\cdot j},\Theta_{\cdot j}\right)=\begin{cases}1\ if & \forall i\neq SPX,\Theta_{ij}>2/3\\ \frac{1}{2}\sum\limits_{i\in\{FF1,FF2\}}\Theta_{ij} & otherwise.\end{cases}$$

In the first case, if shock j explains over 2/3 of movements in all interest rate series, $C_{FF,j}$ is set to the maximum possible value to virtually ensure labeling as the Fed Funds shock; otherwise, $C_{FF,j}$ is the average of Θ_{ij} over the two first Fed Funds futures contracts.

For the forward guidance shock,

$$C_{FG,j}\left(S_{\cdot j},\Theta_{\cdot j}\right)=\begin{cases}1\ if & \forall i\in s_R,\Theta_{ij}>2/3\\ \min_{i\in s_{ED}}\left(\mathbf{1}\left[S_{_{ij}}\neq S_{SPXj}\right]\right)\frac{1}{4}\sum\limits_{i\in\{s_{ED},SPX\}}\Theta_{ij} & otherwise,\end{cases}$$

where $s_{ED}=\{ED6,ED7,ED8\}$ denotes the set of longer Eurodollar (ED) rates and $s_R=\{s_{ED},T5,T10\}$, adding longer Treasury yields. In the first case, if shock j explains over 2/3 of movements of longer-term interest rates (as proxied by s_R), $C_{FG,j}$ is set to the maximum value. Otherwise, provided that interest rate expectations around the two-year horizon (proxying for forward guidance) all move in the opposite direction to the S&P 500, as expected for "Odyssean" guidance, $C_{FG,j}$ is the average of Θ_{ij} across ED rates near the two-year horizon and the S&P 500. If rates and the S&P 500 move in the same direction, $C_{FG,j}$ is set to zero.

For the asset purchase shock, I allow for the fact that such policies may move Treasury yields of different maturities in different directions. If both the 5- and 10-year Treasury move in the same direction, $s_T=\{T5,T10\}$. Otherwise, let s_T be whichever has larger Θ_{ij}. Then,

$$C_{AP,j}\left(S_{\cdot j},\Theta_{\cdot j}\right)=\max_{i\in s_T}\left(\mathbf{1}\left[S_{_{ij}}\neq S_{SPXj}\right]\right)\frac{1}{|s_T|+1}\sum_{i\in\{s_T,SPX\}}\Theta_{ij},$$

which, provided that the Treasury yields in s_T move in opposite directions to the S&P 500, as expected for an asset purchase shock, takes the average of Θ_{ij} over s_T and the S&P 500, and otherwise is equal to zero.

For the Fed information shock,

$$C_{FI,j}\left(S_{\cdot j},\Theta_{\cdot j}\right)=\min_{i\in s_R}\left(\mathbf{1}\left[S_{_{ij}}=S_{SPXj}\right]\right)\frac{1}{6}\sum_{i\in\{s_R,SPX\}}\Theta_{ij},$$

which, provided the S&P 500 and all long rates move in the same direction, as expected for a Fed information shock (see e.g., the identification approach of Jarociński and Karadi (2020)), is equal to the average of Θ_{ij} over all long rates and the S&P 500, and otherwise equal to zero.

Having computed $C(S, \Theta)$, I search across all combinations of shock-label pairs for the combination of k_{mp} shocks and labels for which the sum of the corresponding elements of C is maximized, under three additional restrictions. First, there are no asset purchase shocks prior to December 2008, when such purchases were first mentioned in an FOMC statement. Second, if the front Fed Funds future rate varies by less than a basis point and $k_{mp} < 4$, I restrict there to be no Fed Funds shock.[15] Third, any selected label-shock pair must correspond to a strictly positive value of C. In the rare case that this restriction is violated (C does not contain k_{mp} strictly positive entries in unique row-column pairs), I first label as many shocks as possible without selecting combinations with weakly negative entries. I then compute an alternative criterion for the remaining label-shock combinations identical to that above except that it omits the indicator functions on the sign of rate and equity movements, replacing Θ_{SPXj} with zero when computing $C_{FG,j}$ and $C_{AP,j}$ (still effectively penalizing for the fact that the movement of equities is in the wrong direction for those shocks) and replaces Θ_{ij} with zero for those interest rates moving in the opposite direction to the S&P 500 when computing $C_{FI,j}$ (again penalizing for the fact that their movement is in the wrong direction). I then label remaining shocks up to k_{mp} using this modified criterion.

E Additional empirical results

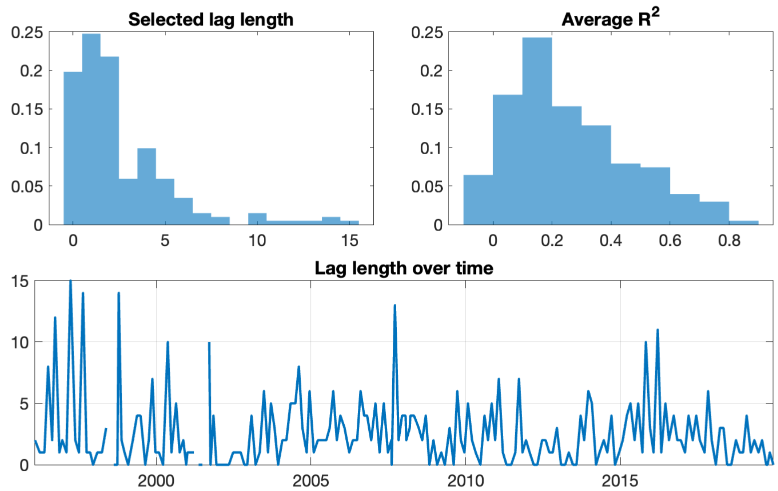
This section reports additional empirical results covering the reduced-form factor models, announcement-specific decompositions, evidence of time-variation in the decompositions, the timeseries properties of the monetary policy shock series the responses of financial variables to the timeseries of shocks, and the Fed information effect.

E.1 Specification details of the reduced-form factor models

In this section, I report statistics on the specifications selected for the reduced form factor models. The left panel of Figure 7 plots a histogram of the lag lengths selected in the VAR models fitted to the factors to remove any remaining predictability, across the 199 datasets. Typically, the selected lags are relatively short, with a median of 2 and mean of

[15] If the announcement date is within 5 business days of the expiry of the front contract, I consider the next month's contract instead.

Figure 7: Specification details from the factor VARs

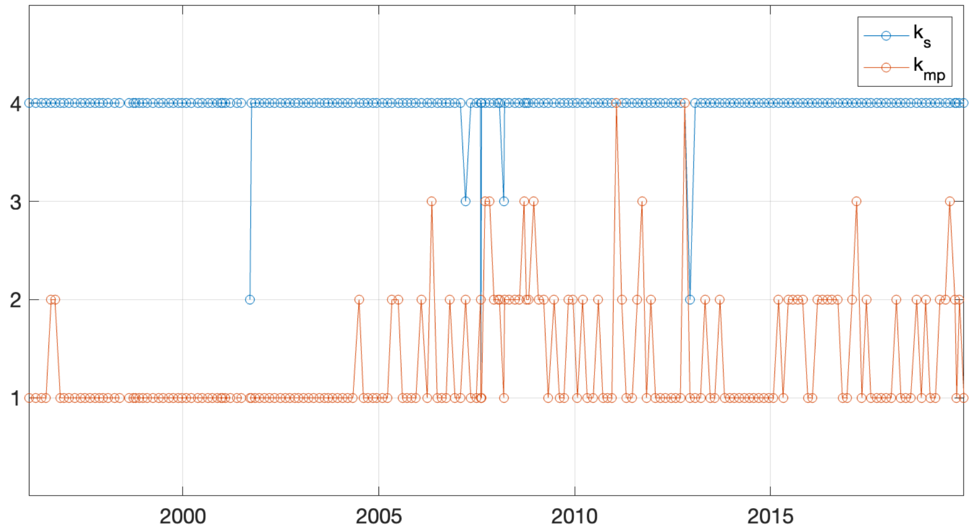


The left panel displays the distribution of the lag lengths selected by the HQ information criterion in the reduced-form VARs fitted to the factors across the 199 datasets considered. The right panel displays the average R^2 from the same VARs, with a simple average taken across the R^2 for each individual factor. The bottom panel plots the selected lag length over time.

2.52, reflecting low predictability of high-frequency asset price movements. However, there are some days in the sample for which the selected lag length is considerably longer, reflecting greater predictability. The second panel reports the average R^2 in the reduced-form VARs fitted to the sets of k_s factors across the 199 datasets. The R^2 is generally quite low, with a median of 0.21 and mean 0.25, reflecting that the majority of variation in the factors is in fact unpredictable, leaving rich information from which to recover the monetary policy shocks. The bottom panel plots the selected lag length over time. The distribution of lag lengths does not appear to have changed dramatically over the sample, with the exception that the models with particularly long lag lengths seem to be concentrated at the beginning, in the late 1990s.

Figure 8 plots the dimension of the estimated VAR in principal components and the dimension of monetary policy across announcements. The former is k_s, the number of identifiable shocks (up to four), based on a Cragg-Donald test for the information contained in the time-varying volatility. The latter is determined by the dimension of the common component of the asset prices, k_{mp}, estimated using the BIC_2 criterion of Bai and Ng (2002). For all announcements, $k_s \geq k_{mp}$, meaning all monetary policy shocks are identifiable. The reason for then estimating models of size k_s, and not just k_{mp}, is to allow for the possibility that additional non-monetary policy shocks, for example microstructure noise, may be driving the innovations to the principal components, η_m. If that is the case, but a model of dimension k_{mp} was assumed, the model would be non-invertible. In essence, this allows

Figure 8: The dimension of estimated models and dimension of monetary policy



The blue line plots the dimension of the model (number of principal components entering the VAR) for each announcement, which is determined by the number of identifiable shocks (with an upper bound of four), k_s. The red line plots the dimension of monetary policy, equal to the dimension of the common component, k_{mp}.

one final check on the role of (microstructure) noise, by allowing some of the variation in η_m to be discarded as not relevant to monetary policy. The number of total identifiable shocks in the model is fairly stable over the sample, most often at 4, the maximum allowed. As a consequence, the number of noise shocks is highest earlier in the sample, when the dimension of monetary policy is lower.

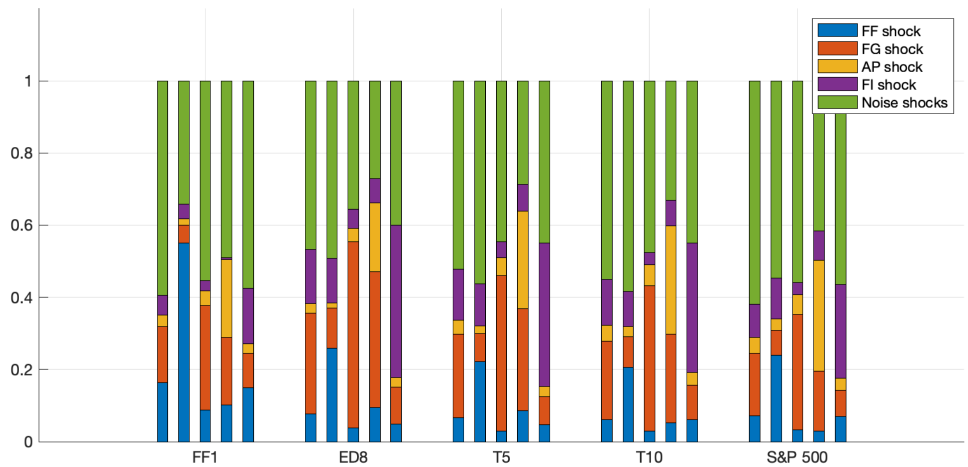
Finally, I further illustrate the role of "noise shocks", in comparison to the labelled monetary policy shocks, in explaining variation in the principle components. In particular, I compute forecast error variance decompositions (FEVDs) for the innovations in the k_s-dimensional principal component VAR (1-step ahead forecast errors). Since there is no natural interpretation of one principal component versus another, I report FEVDs scaled to various asset prices, using the loadings on the principal components. In other words, the results reported can be viewed as FEVDs for the 1-step ahead forecast errors of the portion of the asset prices explained by the first k_s principal components. Note, however, that this variation is not generally the same as that explained by the common component of the asset prices, since in most cases k_s is strictly greater than k_{mp}, meaning that the k_s principal components contain some idiosyncratic variation. Figure 9 plots the results. For each asset price, the first set of stacked bars represents the overall FEVD across all announcements. The second set represents the FEVD for the subset of dates when the Fed Funds shock was active, the third when the forward guidance shock was active, the fourth when the asset purchase shock was active, and the fifth when the Fed information shock was active. The role of noise shocks is clear: across all asset prices and announcements, they explain about 55% of variation in the forecast errors to the k_s principal components at the minute by minute frequency. While this number may seem high, as noted above, for most announcements some of the principal components represent idiosyncratic noise, since $k_s \geq k_m$ (accordingly, the majority of variation in the first principal component, which is always part of the common component, remains explained by the monetary policy shocks). Moreover, the story is quite different when considering the subsets of announcements for which shocks impacting a particular asset price were active. For example, the variation in the front Fed Funds future contract rate explained by noise shocks unsurprisingly declines from nearly 60% to 34% on days when a Fed Funds shock actually occurs, with the majority of the remaining high-frequency variation explained by the high-frequency Fed Funds shocks. Elsewhere, on days when forward guidance shocks occur, about 65% of variation in the 8-quarter ED rate is explained by monetary policy shocks, and when asset purchase shocks occur, around 70% of variation in each of the 8-quarter ED rate, 5-year Treasury yield, and 10-year Treasury yield is explained by monetary policy shocks.

This analysis demonstrates three points. First, the role of noise shocks is non-trivial, such that ignoring the possibility that not all of the variation in the first k_s principal components is driven by monetary policy shocks could prevent accurate identification of monetary policy shocks (since related asset prices could be impacted by related sources of microstructure noise). Second, these high-frequency FEVDs help to validate the labeling of the monetary policy shocks, which is based on the aggregated shocks via historical decompositions, and not the 1-step ahead forecast errors entering the FEVDs. In particular, each monetary policy shock has the expected FEVD profile, with the Fed Funds shock driving short Fed Funds futures, but also impacting all other asset prices; forward guidance driving the 8-quarter ED rate, but also impacting long Treasury yields and the S&P 500; asset purchases driving Treasury yields, when active, while having a small effect on the 8-quarter ED rate (consistent with the signaling channel); and the Fed information shock contributing strongly to all prices except for short Fed Funds futures. Finally, to the extent that the share attributed to noise shocks is still considered to be high, these results suggest that my monetary policy shock series may be seen as conservative, with shocks that do not have a strong enough effect across the panel of asset prices discarded as noise.

E.2 Announcement-specific decompositions

In this section I report details of the key announcement dates considered in the text, provide additional summary statistics for the decompositions across announcements, present sensi-

Figure 9: Forecast error variance decompositions of the principal components



Each stacked bar represents a forecast error variance decomposition (FEVD) for the one-step ahead forecast error of the k_s principal components, scaled by the loadings of the various indicated asset prices. For each asset price, the first set of stacked bars represents the overall FEVD across all announcements. The second set represents the FEVD for the subset of dates when the Fed Funds shock was active, the third when the forward guidance shock was active, the fourth when the asset purchase shock was active, and the fifth when the Fed information shock was active.

tivity analysis of the decompositions for key announcement dates, and conduct a placebo test of my identification approach.

Table 4 reports details of the content of the 12 key announcements covered in detail in the text. It is largely copied from Swanson (2021), with 2 announcements added.

Table 5 reports summary statistics across the full set of 199 announcements. The first panel reports results for the conventional 30-minute window and the second for 10 minutes prior to an announcement through market close. The results document the fact that examining simple event-study style changes in relevant asset prices (δY_i) would generally overstate the size of shocks, relative to decompositions taking seriously the role of multiple shocks for a single asset price, by conflating such shocks. These results also suggest that the scale of decompositions is generally weakly larger when the end-of-day window is considered. However, this obscures considerable heterogeneity across announcements. The final columns of each panel indicate the number of announcements passing thresholds of "economic significance" (using standard deviations of the respective asset prices in the hours following monetary policy announcements instead of standard errors, given the difficulty of inference on historical decompositions).

Figure 10 plots the historical decompositions for the 12 key announcement dates with respect to intraday shocks identified using the Rigobon (2003) regime-based identification approach. For ease of comparison, for each announcement I assume that the number of identifiable shocks is the same as in the baseline; however, formal tests based on Lütkepohl et al. (2020) suggest that this may not be the case. Broadly speaking, the results are very similar to the baseline. The main differences are that the asset purchase shock in September 2013, when tapering was delayed, is no longer significant, and the December 2012 Fed information shock is relabeled as a forward guidance shock (the introduction of calendar based guidance).

Figure 11 plots historical decompositions for 10 placebo dates. These dates are chosen to correspond to the 10 largest macroeconomic surprises for advance GDP and ADP employment releases (measured using Bloomberg consensus forecasts) during the sample. This poses a stern test, as these are certainly major news events, followed closely by markets, so may impact interest rates and equities, but are not monetary policy shocks. One would expect that shocks will exist on these days, but they should either be labeled as "Fed information shocks", which after all share the characteristics of macroeconomic news shocks more broadly, or else be insignificant. This is indeed the case. Table 6 reports the hypothetical end-of-day responses of the front Fed Funds future to the Fed Funds shock, the 8-quarter ED rate to the forward guidance shock, the 10-year Treasury yield to the asset purchase shock, and the S&P 500 return to the so-called Fed information shock. 8 of the 10 identified shocks across the 10 days are labeled as Fed information shocks. No other shock has a non-trivial effect on its reference price.

E.3 Time-variation in the decompositions

Figure 12 displays the relative end-of-day response of 5-year and 10-year Treasury yields to the asset purchase shock. The 5-year response is normalized by the 10-year response, which is fixed at 1. This plot shows that there is considerable variation in the relative responses, including sign changes, commensurate with the different focuses of announcements from one cycle to the next, often with different impacts on different points on the yield curve.

Figure 13 goes a step further to provide more formal support for the use of announcement specific decompositions. It assesses the stability of the relative impacts of the monetary policy shocks at the end-of-day horizon. These end of day responses represent the object of interest in a typical pooled-data event study methodology. Under the assumption of stable relative impacts through time, the relative responses should be identical from one announcement to the next. To test this hypothesis, I conduct rolling-window regressions of pairs of responses to a given shock. If the relative impacts are constant over time, the rolling window regression coefficients should be fixed and identical to the homogeneous (full sample) regression coefficients. I report the results of a set of such regressions in Figure 13, using 40-announcement rolling windows (approximately 5 years) along with 68% heteroskedastic-

Table 4: Key FOMC announcements 2008-2015

December 2008	FOMC announces that it has cut the FFR to between 0 and 25 basis points (bp), will purchase large quantities of agency debt and will evaluate purchasing long-term Treasuries
March 2009	FOMC announces it expects to keep the federal funds rate between 0 and 25 bp for "an extended period", and that it will purchase $750B of mortgage-backed securities, $300B of longer-term Treasuries, and $100B of agency debt (a.k.a. "QE1")
November 2010	FOMC announces it will purchase an additional $600B of longer-term Treasuries (a.k.a. "QE2")
August 2011	FOMC announces it expects to keep the federal funds rate between 0 and 25 bp "at least through mid-2013"
September 2011	FOMC announces it will sell $400B of short-term Treasuries and use the proceeds to buy $400B of long-term Treasuries (a.k.a. "Operation Twist")
January 2012	FOMC announces it expects to keep the federal funds rate between 0 and 25 bp "at least through late 2014"
September 2012	FOMC announces it expects to keep the federal funds rate between 0 and 25 bp "at least through mid-2015", and that it will purchase $40B of mortgage-backed securities per month for the indefinite future
December 2012	FOMC announces it will purchase $45B of longer-term Treasuries per month for the indefinite future, and that it expects to keep the federal funds rate between 0 and 25 bp at least as long as the unemployment remains above 6.5 percent and inflation expectations remain subdued
September 2013	FOMC announces that it will wait to taper asset purchases
December 2013	FOMC announces it will start to taper its purchases of longer-term Treasuries and mortgage-backed securities to paces of $40B and $35B per month, respectively
December 2014	FOMC announces that "it can be patient in beginning to normalize the stance of monetary policy"
March 2015	FOMC announces that "an increase in the target range for the federal funds rate remains unlikely at the April FOMC meeting"

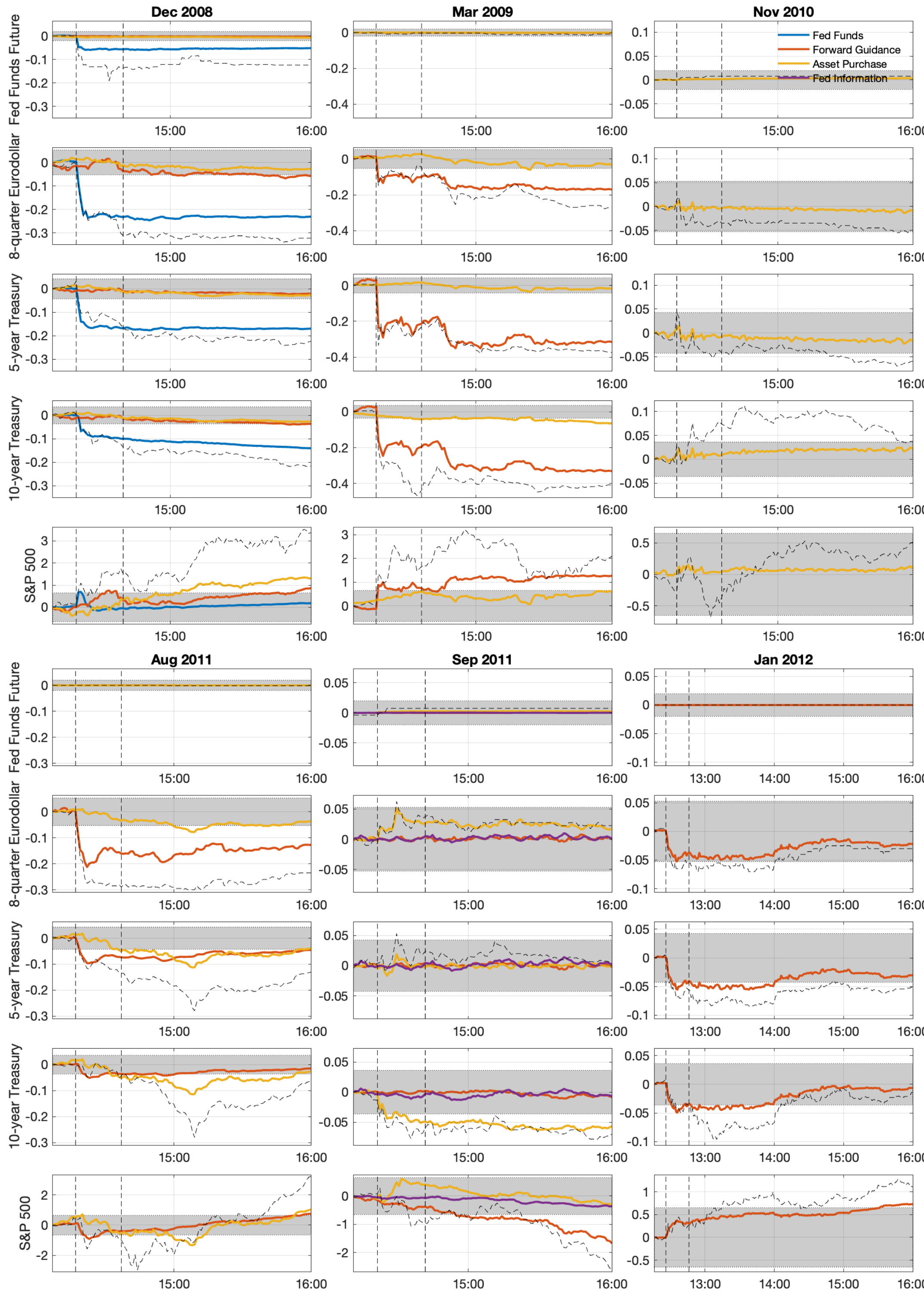
This table is replicated from Swanson (2021), with the addition of details on the December 2008 and September 2013 announcements.

Table 5: Summary statistics for historical decompositions

	30-minute window						end-of-day window					
	mean $\lvert\delta Y_i\rvert$	median $\lvert\delta Y_i\rvert$	mean decomp.	median decomp.	1.96 s.d.	2.58 s.d.	mean $\lvert\delta Y_i\rvert$	median $\lvert\delta Y_i\rvert$	mean decomp.	median decomp.	1.96 s.d.	2.58 s.d.
$FF1, FF$	0.01	0.00	0.01	0.01	9	6	0.02	0.00	0.02	0.01	17	12
$FF1, FG$			0.00	0.00	1	1			0.00	0.00	3	1
$FF1, AP$			0.00	0.00	1	1			0.00	0.00	1	1
$FF1, FI$			0.00	0.00	0	0			0.00	0.00	0	0
$ED8, FF$			0.02	0.01	5	3			0.03	0.02	5	4
$ED8, FG$	0.04	0.03	0.04	0.02	25	14	0.06	0.04	0.04	0.02	29	18
$ED8, AP$			0.01	0.01	0	0			0.01	0.01	1	0
$ED8, FI$			0.02	0.01	6	0			0.02	0.01	10	5
$T5, FF$			0.02	0.01	6	2			0.02	0.01	5	4
$T5, FG$			0.03	0.02	21	15			0.03	0.02	26	18
$T5, AP$	0.04	0.02	0.01	0.00	1	0	0.05	0.04	0.02	0.01	3	1
$T5, FI$			0.01	0.01	5	3			0.02	0.01	9	6
$T10, FF$			0.01	0.01	4	3			0.02	0.01	7	5
$T10, FG$			0.02	0.01	19	9			0.02	0.01	17	11
$T10, AP$	0.03	0.02	0.01	0.00	3	2	0.43	0.03	0.02	0.01	4	3
$T10, FI$			0.01	0.01	5	3			0.01	0.01	7	4
SPX, FF			0.20	0.09	4	3			0.35	0.16	11	8
SPX, FG			0.19	0.11	5	4			0.29	0.14	13	8
SPX, AP			0.14	0.08	1	0			0.27	0.11	3	3
SPX, FI	0.37	0.24	0.11	0.05	0	0	0.75	0.47	0.21	0.11	6	3

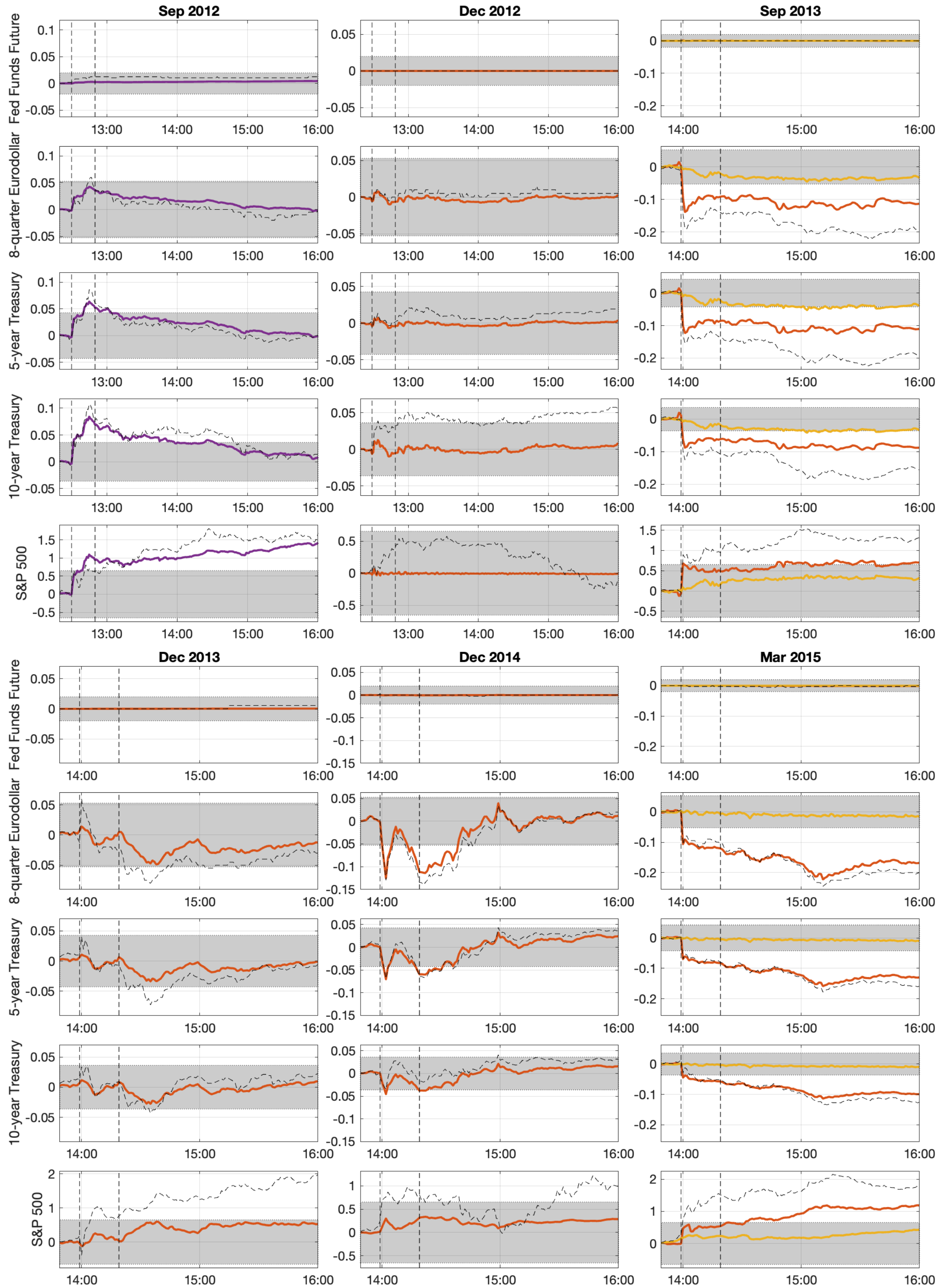
Summary statistics for the historical decompositions of each rate with respect to the three shocks; the left panel considers the decomposition based on shocks occurring between 10 minutes prior to the announcement and 20 minutes following, and the bottom considers 10 minutes prior until 4:01pm. The units are percentage points. The first two columns summarize the absolute values of the simple change in the asset price over the window. The next two columns repeat the exercise for the absolute value of the historical decompositions. The final two columns report the number of decompositions with respect to the given shock that exceed multiples of the average standard deviation in the interest rate following monetary policy announcements.

Figure 10: Historical decompositions of key FOMC announcements: regime approach



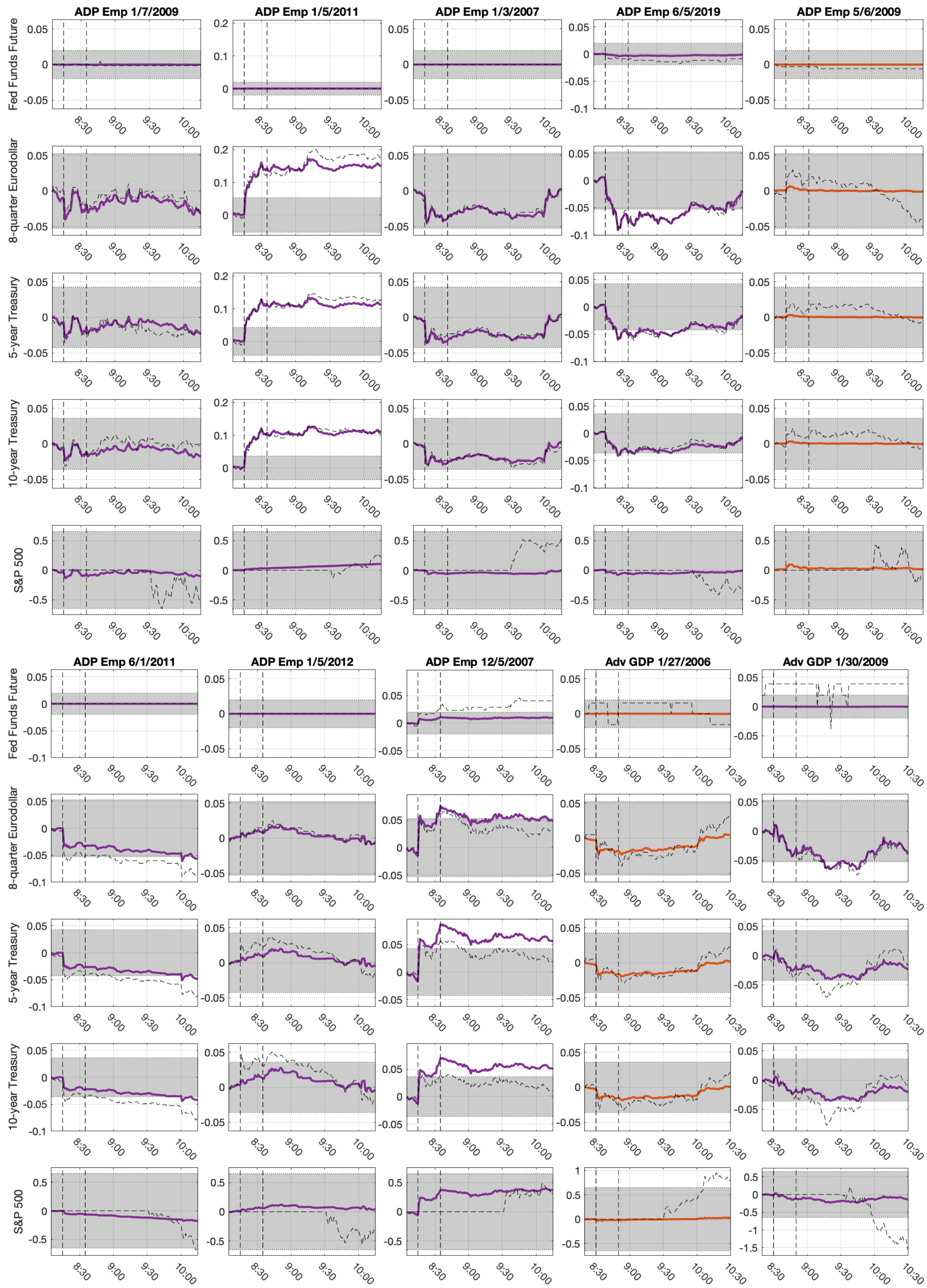
Historical decompositions for the rate series indicated in the left margin with respect to each of the four shocks, identified using the Rigobon (2003) variance regimes approach. Blue represents the Fed Funds shock, red the forward guidance shock, gold the asset purchase shock, and purple the Fed information shock. The shaded interval corresponds to 1.96 times the average standard deviation in the asset price following monetary policy announcements. The vertical lines mark the time of the announcement and 20 minutes following the announcement, the end of the conventional analysis window. The black dashed line is the path of the simple change from ten minutes prior to the announcement, the event study estimate. Units are percentage points.

Figure 10b: Historical decompositions of key FOMC announcements: regime approach (cont'd)



See Figure 10 for notes.

Figure 11: Historical decompositions for placebo dates



Historical decompositions for the rate series indicated in the left margin with respect to each of the four shocks for placebo dates corresponding to the hours following the 10 largest macroeconomic surprises for advance GDP and ADP employment releases from 1996-2019 (as measured by Bloomberg consensus forecasts). Blue represents shocks labeled as a Fed Funds shock, red a forward guidance shock, gold an asset purchase shock, and purple a Fed information shock. The shaded interval corresponds to 1.96 times the average standard deviation in the asset price following monetary policy announcements. The vertical lines mark the time of the announcement and 20 minutes following the announcement, the end of the conventional analysis window. The black dashed line is the path of the simple change from ten minutes prior to the announcement, the event study estimate. Units are percentage points.

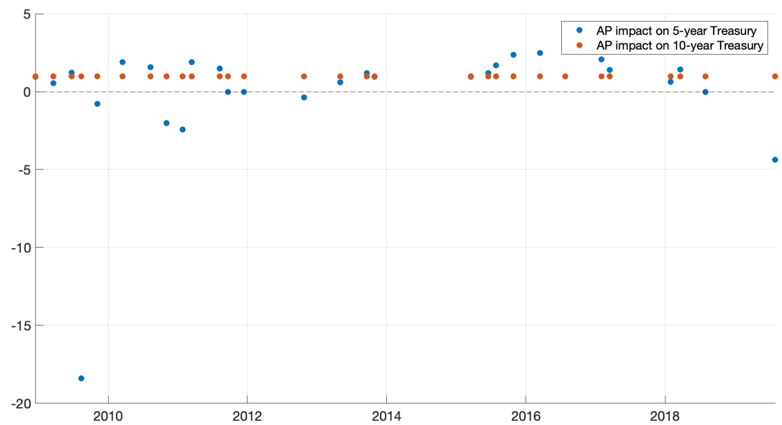
Table 6: Responses of reference prices on placebo days

	ADP Emp. 1/7/2009	ADP Emp. 1/5/2011	ADP Emp. 1/3/2007	ADP Emp. 6/5/2019	ADP Emp. 5/6/2009	ADP Emp. 6/1/2011	ADP Emp. 1/5/2012	ADP Emp. 12/5/2007	Adv. GDP 1/27/2006	Adv. GDP 1/30/2009
$FF1, FF$	--	--	--	--	--	--	--	--	--	--
$ED8, FG$	--	--	--	--	0.00	--	--	--	0.00	--
$T10, AP$	--	--	--	--	--	--	--	--	--	--
SPX, FI	-0.11	0.11	0.00	-0.01	--	-0.18	0.04	0.37	--	-0.13

End-of-day responses computed using historical decompositions following the baseline model for placebo dates corresponding the 10 largest macroeconomic release surprises to advance GDP and ADP employment (based on Bloomberg consensus forecasts) from 2007-2019.

ity robust confidence intervals for both rolling window and homogeneous coefficients. The value for a given date corresponds to the coefficient based on the previous 40 observations, inclusive. The first column of plots considers responses to the forward guidance shock, relative to that of the 8-quarter ED rate. In general, the responses do not deviate too far from the homogeneous coefficients. However, there is evidence of stronger relative effects on both Treasury yields and the S&P 500 during the early 2000s and an increase in the responsiveness of Treasury yields during the ZLB period (although these changes are generally not statistically significant). There is more considerable time variation in the effects of asset purchases, reported in the second column relative to the response of the 10-year Treasury yield. The relative responses of both the 8-quarter ED rate and 5-year Treasury yield rise steadily over the course of the sample, and the 68% confidence intervals do not overlap with that of the homogeneous coefficients after late 2016. This break coincides with the pre-Operation Twist period dropping out of the rolling windows. While less dramatic, the relative impact on the S&P 500 also increases over the same period. The third column considers the impact of information shocks, relative to the response of the S&P 500. The effects of the Fed information shock appear to be more volatile. Impacts are large on the 8-quarter ED and 5-year Treasury in the early 2000s. The responsiveness of all three asset prices rises following the onset of the Great Recession, before falling from 2013 through 2015 and rising again subsequently. This is consistent with markets paying greater attention to any indication about the state of the economy contained in FOMC statements during the height Great Recession. At various points, the confidence intervals do not overlap with those of the homogenous coefficients. These preliminary tests provide some evidence of time variation in the relative impacts of monetary policy shocks on various asset prices, and thus call into question the standard assumption of a single time-invariant decomposition of asset prices movements into monetary policy shocks.

Figure 12: Variation in the effects of the asset purchase shock



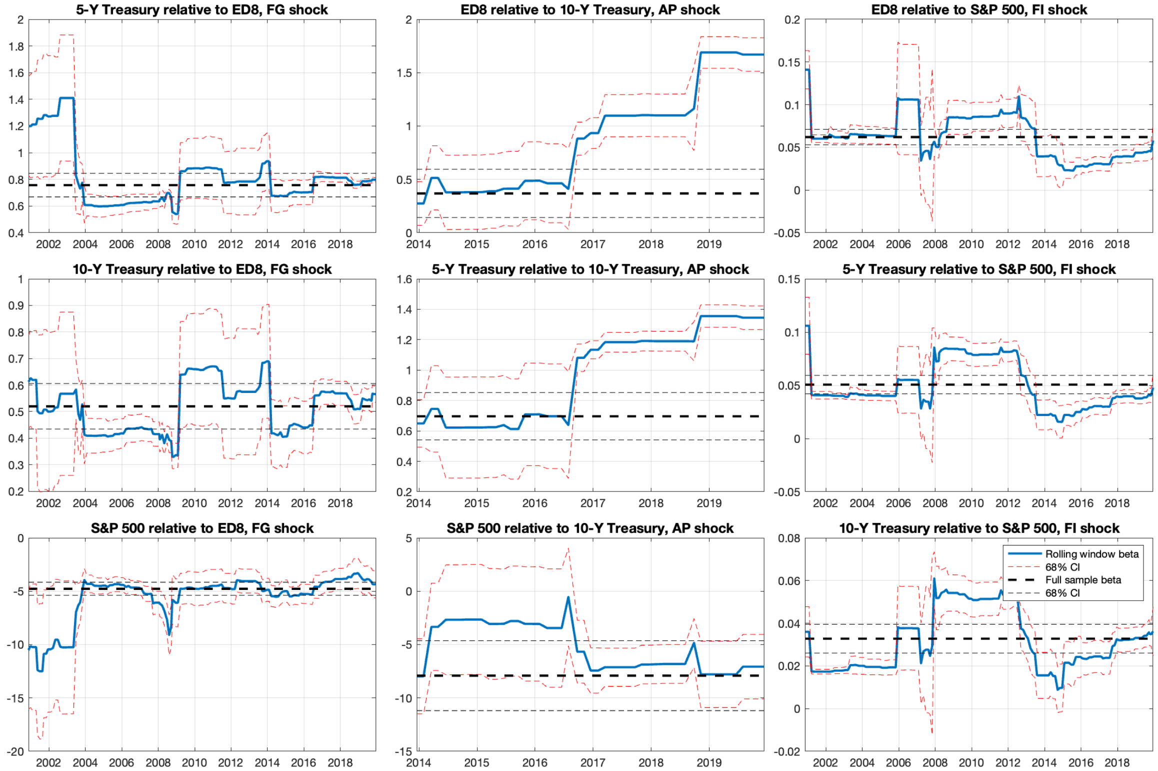
The end-of-day impact of the asset purchase shock on the 5-year Treasury yield is normalized by its impact on the 10-year Treasury yield, which is fixed at one.

Additionally, policy discussions have speculated whether the effects of asset purchases may have decreased over time. To explore this possibility, I compute an R^2-type measure of the share of variation explained by asset purchase shocks based on the historical decompositions. In particular, I take the historical decomposition of the 10-year Treasury yield with respect to the asset purchase shock as the predicted value, compute the error relative to the actual path of yields, and use these errors and actual values to compute an R^2. Conditional on the sample of dates for which asset purchase shocks actually occurred, the R^2 is 0.41. For the December 2008-2013 subsample , the value is 0.42, and for 2014-2019, the value is 0.25. Thus, there is evidence that asset purchases have indeed become less effective over time, although the number of observations in these subsamples is small, so the results should be treated with caution.

E.4 Additional comparison of shock series

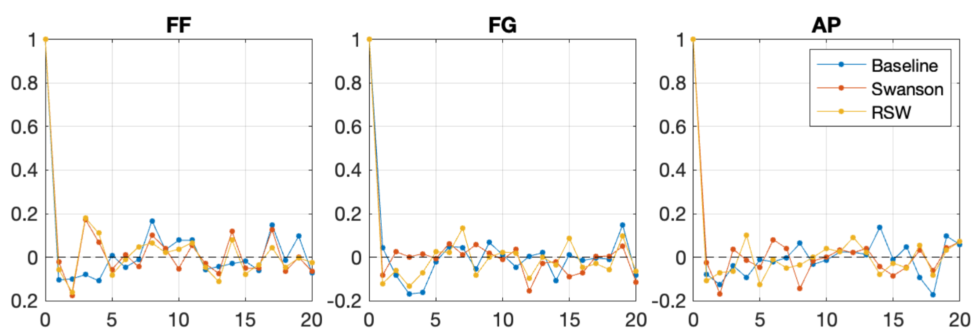
In this section, I report additional properties of my shock series, compared to the Swanson and RSW shocks. Figure 14 reports the autocorrelation functions of each shock series. The main features of each series are qualitatively similar, with relatively low persistence from the first lag onwards. These properties do not provide an obvious explanation for the different responses found for the RSW series in Section 4.3. Figure 15 plots impulse response of Treasury yields to each shock series at horizons from 0-20 business days, essentially a month. The effects of the shocks on Treasury yields appear remarkably similar, suggesting similar transmission to interest rates. Moreover, the effects of the various shocks across different maturities accord well with theory. Any differences in the macroeconomic effects do not appear to stem from this channel.

Figure 13: Time variation in relative effects of shocks



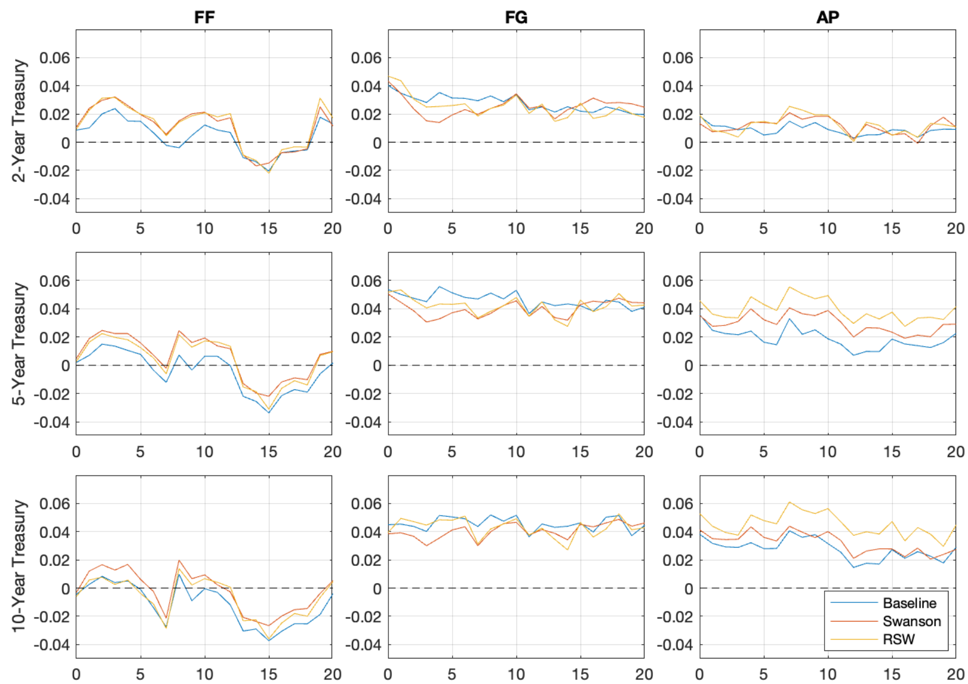
Each panel plots the evolution of the relative effects of the stated shock on two asset prices over time. The blue line plots the 40-announcement (approximately 5-year) rolling-window regression ending at the given date of the end-of-day response of the first asset price to the end-of-day response of the second asset price. The dashed red lines indicate the 68% confidence interval based on HAC standard errors. For reference, the bold dashed black lines plot the full sample homogeneous coefficient and the light dashed black line plots its 68% heteroskedasticity-robust confidence interval.

Figure 14: Autocorrelation functions of alternative shock series



Autocorrelations of the baseline shocks, alongside those of Swanson (2021) and Rogers et al. (2018). The sample spans January 1996 until the last available period for the respective series.

Figure 15: Impulse responses of Treasury yields to alternative shock series



Impulse responses estimated for horizons ranging from zero to 20 business days estimated via local projection without controls, as in Swanson (2021), for 1 standard deviation shocks. The sample spans 1996-2019, or the last period available for the alternative shock measures.

E.5 Responses of financial variables during the ZLB period

Table 7 repeats the regressions of Table 3 in the main text for the ZLB period, as defined in Swanson (2021), 2009-2015. The results largely accord with those for the full sample, as noted in the text.

E.6 The role of the Fed information effect

In this section, I use an alternative model to establish the role of the Fed information effect, documented by Campbell et al. (2012), Nakamura and Steinsson (2018), Jarociński and Karadi (2020), and Lunsford (2020), amongst others. The presence of an information effect has recently been questioned by Bauer and Swanson (2022), who argue that evidence based on the response of survey expectations is consistent with both the Fed and private forecasters reacting to the same public information, rather than the Fed revealing new information via its statements. The alternative model that I consider omits the S&P 500 from the panel of data used to extract the principal components and allows only up to three dimensions of monetary policy: the Fed Funds, forward guidance, and asset purchase shocks. In doing so, it assumes that there is no Fed information effect. Comparing these results to those under

Table 7: Financial market responses to monetary policy

	AAA yield	AAA spread	Baa yield	Baa spread	TIPS spread	JPY/ USD	Euro/ USD	VIX
FF	4.64***	0.47	3.16***	-1.00	-1.80**	6.69	1.93	-215.71
FG	0.44**	-0.52***	0.38*	-0.58***	-0.23**	1.20	1.47**	53.27*
AP	1.02*	-1.02***	1.32*	-0.72	-0.23	2.63	0.00	-59.75
FI	0.05	0.00	0.07**	0.02	0.06**	-0.34	-0.10	-16.20***

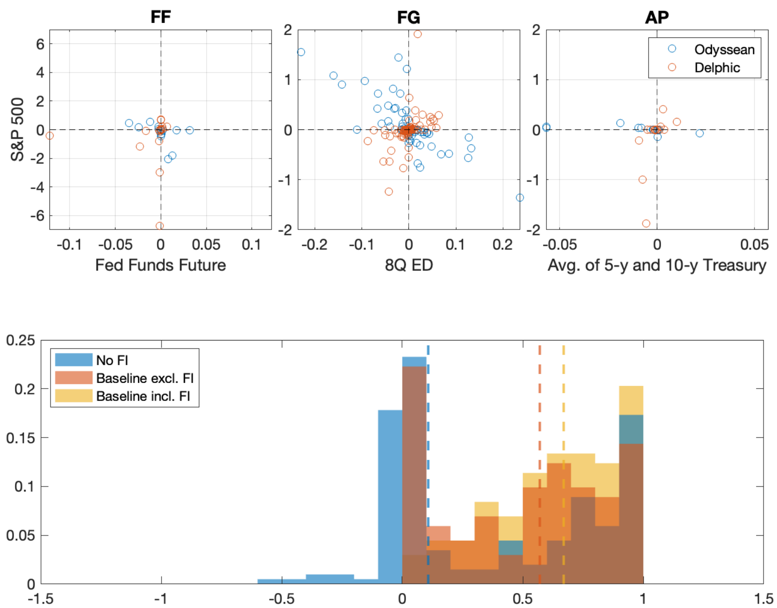
Coefficients are estimated following equation (8) . Coefficients can be interpreted as the response in percentage points to a shock that changes the reference price by 1%. The sample spans the ZLB period, 2009-2015. HAC standard errors are calculated following Lazarus et al. (2018). Significant results are starred at the 10%, 5% and, 1% levels.

the baseline model, I show support for the presence of the Fed information effect.

While the S&P 500 is not included in the panel of data used to estimate the principal components, I can still construct historical decompositions for equities by projecting the path of stock returns on the extracted components. The first panel of Figure 16 displays scatter plots of the end-of-day decompositions of the S&P 500 against the values of the three monetary policy shocks, which are themselves end-of-day decompositions for various interest rates. The blue circles plot observations that are consistent with “Odyssean” policy shocks – moving equities and interest rates in opposite directions – while the red circles plot observations that are consistent with "Delphic" policy, or information effects. For all three dimensions of policy, not just forward guidance, there are numerous instances whose signs are characteristic of an information effect. This exercise and its results parallel the findings of Lunsford (2020), who observes that the effects of forward guidance appear time-varying when “Delphic” effects are included. This analysis can be formalized in a regression of end-of-day decompositions on the shock measures, as in Table 2. Table 8 compares the impacts to those in the baseline model. For all three dimensions of policy, the previously large, negative effects are attenuated. The average effect of the Fed Funds shock remains negative, but becomes insignificant. The forward guidance shock retains a significant negative effect, but the magnitude is smaller. The point estimate for the asset purchase shock is the most dramatically changed, now positive, and insignificant. Not allowing for the presence of information effects significantly reduces the measured effects of monetary policy on equities. These results contrast with regressions in Bauer and Swanson (2022), where the sign and magnitude of the S&P 500 response to the Nakamura and Steinsson (2018) monetary policy news shock are not sensitive to whether observations characterized by information effects, on the basis of Blue Chip forecast responses, are included. While the Blue Chip forecast response to announcements has long been used to characterize information effects, the well-known survey timing issues described by Bauer and Swanson (2022) introduce considerable

Figure 16: The role of the Fed information effect

(a) Impact of monetary policy on equities and interest rates



(b) Share of S&P 500 movement explained

The first panel plots the end-of-day responses of the S&P 500 to monetary policy shocks in the model estimated without a Fed information effect against the monetary policy measures, which are end-of-day decompositions of interest rates. Events matching "Odyssean" policy are marked in blue, and those matching "Delphic" policy are in red. The second panel plots the distributions of the difference between the realized path of the S&P 500 and the paths predicted by various historical depositions: based on all shocks for the model with no Fed information shocks (blue), excluding the Fed information shock in the baseline model (red), and including the Fed information shock in the baseline model (gold). The scale of these errors is standardized to an R^2-type measure, as described in the text (so a value of 1 corresponds to perfect explanatory power). The vertical lines plot the medians of each distribution. The x-axis is to the left truncated for readability.

noise and potentially important additional public information, forming the basis for that paper's alternative explanation. Bauer and Swanson (2022) find that the survey response often contradicts the high-frequency S&P 500 response, and the conflicting results here based instead on the S&P 500 further suggest higher-frequency market-based measures of information effects may be desirable.

Next, I examine how allowing for an information effect affects the explanatory power of interest rate movements for equities. For each announcement, I compute the historical decomposition of S&P 500 returns with respect to all three monetary policy shocks to measure the total explained movement at market close, subtract it from the total observed movement over the same window, and divide the square of this error by the square of the observed movement. Finally, I subtract this unexplained share from 1, obtaining an R^2-like measure. If the shocks perfectly explain the movements of equities, the value should be equal to 1 for each announcement. The second panel of Figure 16 plots the distribution

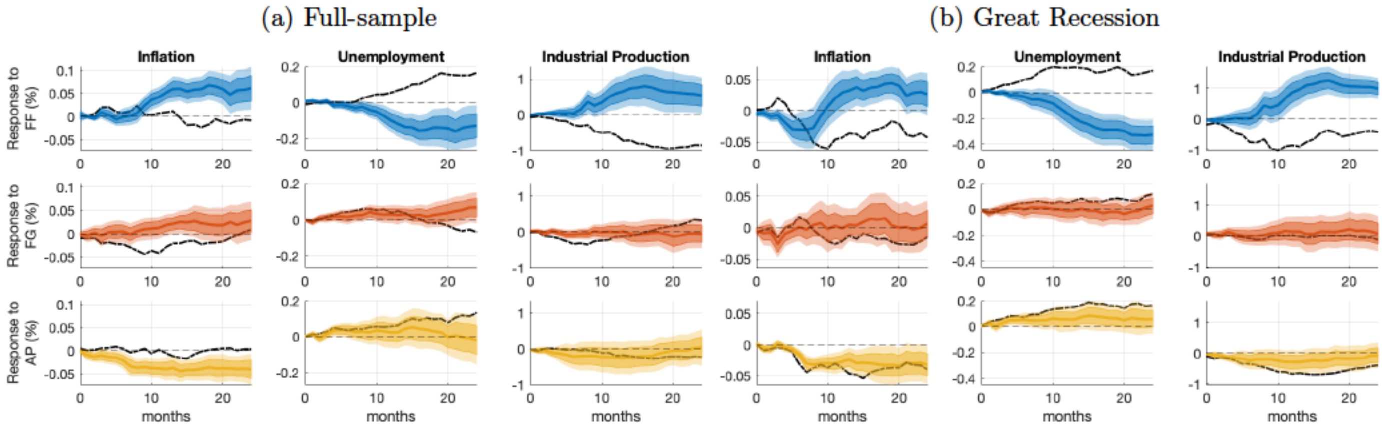
Table 8: End of day effects on the S&P 500

	No Fed Information	With Fed Information
ϵ_{FF}	-2.16	-5.35
ϵ_{FG}	-3.90***	-4.77***
ϵ_{AP}	0.24	-11.04**
ϵ_{FI}	—	1

Regressions of the end-of-day decomposition of S&P 500 returns with respect to a given shock on the decomposition of the reference price with respect to the same shock. The reference rates are the 8-quarter ED for forward guidance, the average of 5- and 10-year Treasury yields for asset purchases, and S&P 500 returns for Fed information. The left column uses decompositions from a model where the S&P 500 is not included in the panel of asset prices used to estimate principal components and where it is assumed there are at most 3 monetary policy shocks, with no information effect. The right panel replicates the baseline model from Table 3. Coefficients can be interpreted as the response in percentage points to an expansionary shock that changes the reference price by 1%. The sample spans 199 announcements from 2007-2019. HAC standard errors are calculated following Lazarus et al. (2018). Significant results are starred at the 10%, 5% and, 1% levels.

of this measure across announcements. Without allowing for information shocks, in blue, mass is concentrated near zero, with a median of 0.11, so that almost none of the observed movement of equities is explained by the shocks, although there are considerable outliers, for which the monetary policy shocks predict large movements in equities that did not materialize. A substantial mass is negative, indicating the predicted movements are larger than the realized movements. I compare these results to those from my baseline estimates, in red. I do not include the predicted impact of the Fed information shock, but only consider the movement in equities predicted by the same three shocks contained in the first model. The mass is now centered around a median of 0.57 (rising to 0.67 if variation predicted by the Fed information shock is included, plotted in gold), and entirely contained in the [0,1] interval, except for a single outlier. As a more parsimonious summary, I also compute a single R^2-type measure across the sample. Instead of estimating a regression model to produce predicted movements for each announcement, I take the movements predicted by the announcement-specific decompositions, and compute an R^2 comparing these to the realized movements. For the model without information effects, I obtain -0.23; the variance of the predicted movements is actually higher than the realized movements. For the baseline model, with information effects, the R^2 is 0.61 (rising to 0.72 if variation predicted by the Fed information shock is included). Taken together, these results indicate that allowing for information effects leads to monetary policy shocks that better explain variation of equity prices. The number for the baseline model, 0.72, is also considerably higher than the 20% reported by Kroencke et al. (2021) for the two GSS factors, suggesting that allowing for a Fed information shock and announcement-specific decompositions may greatly increase the

Figure 17: Dynamic response of macroeconomic aggregates: no Fed information shocks



Impulse responses are calculated via local projection as in equation (9) using monthly data and shocks estimated assuming the maximal dimension of monetary policy is 3, with no Fed Information shock. The left panel considers the full sample, effectively January 1996 to December 2019, and the right panel uses a Great Recession sample, January 2008 to December 2017. Responses are scaled to a one standard deviation expansionary impulse. 68% and 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

ability of monetary policy shocks to explain stock returns. This result positions the Fed information shock as an alternative to the "risk shift" shock proposed by that paper as a means to explain greater variation in stock prices around monetary policy announcements.

Finally, I estimate the impact of the alternative shock measures, without information effects, on macroeconomic aggregates. Figure 17 plots the results. In the full sample, the Fed Funds shock is clearly contaminated, having significant and incorrectly-signed effects on all variables. The forward guidance shock also has a puzzling positive effect on inflation, and null effect on IP, although the sign of the unemployment effect remains standard. The effects of the asset purchase shock are broadly in keeping with theory. In the Great Recession sample, the inflation response to the Fed Funds shock has a standard sign in the first 9 months, before becoming significantly positive, but responses to unemployment and IP remain counterintuitive, consistent with information effects. The effects of forward guidance are effectively null, while the impact of asset purchases is attenuated relative to the baseline model. Taken together, these results point towards the shocks, particularly Fed Funds and forward guidance, being contaminated by information effects. Interestingly, these results are qualitatively similar to those obtained using the RSW shock measures, suggesting that the surprising responses from that exercise may be due to that model also not accounting for information effects.

The dynamic effects of the Fed information shock included in the baseline series also provide new evidence for the information effect. In particular, the information shocks predict actual improvements in economic conditions, entirely apart from the effects on expectations, asset prices, and survey respondents on which most of the literature has previously focused. Even if it is the case that professional forecasters do not pay attention to Fed statements and the Fed reacts to similar public information to private forecasters, there appears to be some content in the statements that passes through to equity prices and subsequently predicts positive macroeconomic developments. This finding parallels that of Jarociński and Karadi (2020) in a model with a single dimension of policy, plus an information effect.

To address their "Fed Response to News" channel, Bauer and Swanson (2022) recommend orthogonalizing monetary policy shocks to macroeconomic releases from the month of the announcement to purge them of any information effect. If their explanation is correct, then there should no longer be any information effect-type content in the shocks. The preceding local projections specification already include lagged macroeconomic releases, like those that Bauer and Swanson (2022) suggest, as controls. However, to further test their hypothesis, I reestimated the baseline local projections adding the values of inflation, the change in unemployment, and IP growth for the announcement reference month as controls, which reflect contemporaneous conditions, but were not available to markets at announcement time due to the release lag. Using both the baseline shocks and those constructed assuming no Fed information effect, the responses are essentially unchanged (apart from the initial impacts, which are now mechanically zero). For the baseline shock series, this is expected for the first three shocks: they were already purged of information effects during construction. For the information shock, however, this indicates additional information content beyond that contained in that month's macroeconomic releases. Under the Bauer and Swanson (2022) explanation, the responses for the shocks constructed assuming no information effects should now align with theory after including recent macroeconomic releases, which is no more the case than in Figure 17.