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

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Abstract

I propose to identify announcement-specific decompositions of asset price changes into monetary policy shocks exploiting heteroskedasticity in intraday data. This approach accommodates both changes in the nature of shocks and the state of the economy across announcements, allowing me to explicitly compare shocks across announcements. I compute decompositions with respect to Fed Funds, forward guidance, asset purchase, and Fed information shocks for 2007-19. Only a handful of announcements spark significant shocks. Both forward guidance and asset purchase shocks lower corporate yields and uncertainty and raise spreads and equities on impact; Fed information shocks raise yields and lower uncertainty. However, only asset purchase shocks significantly stimulate the macroeconomy, raising inflation and industrial production and lowering the unemployment rate.

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

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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 (2020); 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 (2002) 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 (2020) 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 complication of central bank information shocks, whose role has been highlighted by Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2020), remains unaddressed in models boasting the Fed Funds target, 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
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. The latter is missing from previous papers (e.g., Swanson (2020); 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 scheduled announcement from 2007-2019, 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 throughout the hours 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 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. 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). Such assumptions are at least worth investigating. Finally, I do not require all shocks to be active for each announcement, an important consideration when identifying several dimensions of policy. 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 (2020) 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. Both forward guidance and asset purchase shocks lower corporate yields and uncertainty and raise corporate spreads on impact, while asset purchases lower spreads and forward guidance depreciates the dollar at longer horizons. Conversely, Fed information shocks raise yields and lower uncertainty. These results mirror existing papers including Krishnamurthy and Vissing-Jorgensen (2011), Swanson (2020), 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 (2020) and RSW disentangle forward guidance and asset purchase shocks, neither studies the impact on the real economy. Asset purchases have significant, persistent expansionary effects on inflation, unemployment, and industrial production. In contrast, the forward guidance shock has no significant effect on the macroeconomy; the impact on financial markets detailed above does not transmit to real activity. While there are similarities to what one would obtain using the RSW or Swanson (2020) shocks, there are also important differences. 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 in-
traday comovement 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. 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) is the only paper to possibly allow for the time-varying nature of shocks, using a time-varying parameters model. The findings of Gambacorta et al. (2014) for their balance sheet shock align well with the significant effects I find for my asset purchase shock. Bundick and Smith (2020) extend GSS to estimate the macroeconomic effects of forward guidance during the ZLB. Inoue and Rossi (2020) estimate local projections for two policy dimensions corresponding to the slope and curvature factors from a Nelson and Siegel (2002) decomposition, but they do not interpret these responses as corresponding to particular aspects 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, and characterizes the properties of the time-series of the implied shocks. 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

\[
\eta_{it,\delta} = R_{it,\delta} - E[R_{it,\delta} | \mathcal{F}_{t-\delta}],
\]

(1)
where \( R_{it,\delta} = P_{it} - P_{it-\delta} \) and \( \mathcal{I}_{t-\delta} \) 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, \( E[R_{it,\delta} \mid \mathcal{I}_{t-\delta}] = 0 \), 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, \( \epsilon_{j,t,\delta} \), 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

\[
\eta_d = H\epsilon_d, d = 1, \ldots, D,
\]

where \( \eta_d \) 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 (2020); 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, \( \epsilon_d \), must not change – otherwise there is little reason to assume constant relative effects, \( H \), on \( \eta_d \). 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 $\epsilon_d$, where the weights are the derivative of asset prices $\eta_d$ 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

$$\eta_m = H_d \epsilon_m, \ m = 1, \ldots, M,$$

where $\eta_m$ 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 $\epsilon$ 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 multivariate simplified 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

$$dP(t) = \eta(t) = H_d \epsilon(t),$$

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

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

where $\sigma^2(t)$ is the instantaneous (spot) volatility and $W(t)$ is an $n$ dimensional standard Brownian motion. In this setting, structural shocks $\epsilon_m$ are defined on a $1/M$-spaced grid,

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

where

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

It follows that

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

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 very 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 $\eta_d$

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

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 $\eta_d$, 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 ideal, 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 Appendix 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 (2020) narrative approach to distinguish forward guidance and asset purchase shocks, based on the absence of asset purchase shocks prior to 2009, is not applicable given all shocks come from a single announcement day, mostly post-2009.

These factors lead me to consider statistical identification, in particular identification based on time-varying volatility. Figure 1 demonstrates strong volatility patterns for a representative 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 Appendix 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 \( E [\sigma^2 (t) \sigma^2 (t)'] < \infty \).

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 \( \eta_m \) in terms of the underlying continuous time process \( \sigma^2 (t) \). These assumptions imply that \( \epsilon_m \) is also vector of orthogonal MDSs (with respect to \( \sigma_m^2 \) and information through \( (m - 1)/M \)) with conditional variances \( \sigma_m^2 \) and finite fourth moments, satisfying the requirements in Lewis (2021).

Lewis (2021) argues that the autocovariance of squared innovations, \( \eta_m \), 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, \( \sigma_1^2 \). Let \( H_{12} \) be the parameter of interest. Note that taking the outer product of reduced-form innovations, \( \eta_m \), yields

\[
\begin{align*}
\eta_1 \eta_2 &= H_{11} \epsilon_1^2 + H_{12} \epsilon_2^2 + \epsilon_1 \epsilon_2 + H_{21} \epsilon_1 \epsilon_2 \\
\eta_2^2 &= H_{12} \epsilon_1 \epsilon_2 + 2 H_{21} \epsilon_1 \epsilon_2 + \epsilon_2^2.
\end{align*}
\]

It is clear that \( H_{12} \) could be identified from the ratio of the \( H_{12} \epsilon_2^2 \) and \( \epsilon_2^2 \) terms, but only the values of \( \eta_m \) are observed, and not their separate components. However, a lagged value of \( \eta_2^2 \) can be used as an instrument for \( \epsilon_2^2 \). In particular, using the orthogonality and zero serial correlation of shocks and the fact that \( \sigma_1^2 \) is constant (so has zero autocovariance),

\[
\text{cov} (\eta_1 \eta_2, \eta_2^2) = H_{12} \text{cov} (\epsilon_1^2, \epsilon_2^2) = \text{cov} (\eta_2^2, \eta_2^2) = \text{cov} (\epsilon_2^2, \epsilon_2^2).
\]

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 Appendix B.1, \( \lim_{M \to \infty} M^2 \text{cov} (\epsilon_2^2, \epsilon_2^2) = \text{cov} (\sigma_2^2(t), \sigma_2^2(t - p)) \). Then, \( H_{12} \) is identified as

\[
\lim_{M \to \infty} M^2 \text{cov} (\eta_1 \eta_2, \eta_2^2) = \frac{H_{12} \text{cov} (\sigma_2^2(t), \sigma_2^2(t - p))}{\text{cov} (\sigma_2^2(t), \sigma_2^2(t - p))} = H_{12}.
\]
This is an instrumental variables approach, where the dependent variable is \( \eta_{1m}\eta_{2m} \), the endogenous regressor is \( \eta_{2m}^2 \), and the instrument is \( \eta_{2m}^2(m-pM) \). Provided that the time-varying volatility \( \sigma_i^2(t) \) is persistent (\( \text{cov}(\sigma_i^2(t), \sigma_i^2(t-p)) \neq 0 \) 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 \( \zeta_m = \text{vech}(\eta_m'\eta_m) \), 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 \( \lim_{M \to \infty} ME[\zeta_m] \) and \( \lim_{M \to \infty} M^2 \text{cov}(\zeta_m, \zeta_{m-pM}) \), if at least \( n-1 \) shocks display time-varying volatility with non-zero autocovariance, provided that for no two shocks \( i, j \), \( \text{cov}(\sigma_i^2(t), \sigma_j^2(t-p)) = \text{cov}(\sigma_j^2(t), \sigma_i^2(t-p))' \)

\[
E[\sigma_i^2(t)] E[\sigma_j^2(t)]
\]

Theorem 1 follows from Corollary 2 in Lewis (2021) and infill limits derived in Appendix 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 \( \eta_m \). 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 \( \eta_m \) 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; while 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, in particular those that address the threat of noise in such high frequency data.

I base my analysis on a panel of 20 asset prices. Specifically, the minute-by-minute data, $Y_m$, consist of the first 6 months of Fed Funds futures contract rates, the first 8 months 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 panel considered by Swanson (2020). The first step I take 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, $\Delta Y_m$, standardize to $\Delta \tilde{Y}_m$, and then estimate the first four principal components,
of the data from 10 minutes prior to the announcement (using the timestamp from the first headline appearing on Bloomberg) to 4:01pm, immediately following market close,

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

I recover the first four components to span up to four possible dimensions of monetary policy shocks. Working with the common component 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 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.

I assume that the number of orthogonal monetary policy shocks on a given day 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).¹

For each announcement date, 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:

1. Set $n = 4$.

2. Estimate a VAR for the first $n$ principal components to remove any residual predictability from the series (since $\epsilon_m$ must be a MDS), using the Hannan-Quinn information criterion to select $L$:

$$F_m = b + \sum_{l=1}^{L} B_l F_{m-l} + \eta_m. \quad (7)$$

¹I also considered the remaining 5 information criteria of Bai and Ng (2002) as well as the two rank tests of Onatski (2009). The $BIC_2$ is the only information criterion to choose interior solutions and chooses a weakly greater dimension than the two rank tests (and is thus conservative for my purposes) for all but one of the 104 announcement dates.
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

\[
\text{rank} \left( E \left[ \hat{\zeta}_m \hat{\zeta}'_{m-1} \right] \right) = n,
\]

where \( \hat{\zeta}_m = \text{vech} (\hat{\eta}_m \hat{\eta}'_m) \), which indicates that the autocovariance process of \( \sigma^2_m \) 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, \( \epsilon_m \).

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 common component of asset prices, \( F_m \), exhibits much smoother behaviour than the raw prices, and the innovations \( \eta_t \) I ultimately work with are smoother still. Unfortunately, it is not straightforward to test the suitability of the model directly in this setting, since the reduced-form innovations \( \eta_m \) are linear combinations of the shocks, \( \epsilon_m \), whose volatility is modeled. However, simple regressions of squared innovations \( \eta^2_m \) on \( \eta^2_{m-1} \) do yield significant AR(1) parameters for many announcement dates. Moreover, simulations in Lewis (2021) find this estimator to be robust to misspecification of the volatility process; while calibrated to macroeconomic data, the DGPs in that paper do exhibit high persistence and other properties typical of financial timeseries, making them informative for the present setting.

For all announcements, \( k_s \geq k_{mp} \). I estimate the full \( k_s \) shocks, however, as a final check on high-frequency noise. If the first \( k_s \) principal components remain contaminated by noise, estimating \( k_s > k_{mp} \) shocks potentially allows the monetary policy shocks to be separated from that noise, captured by the remaining shocks (since microstructure noise is known to have intraday volatility patterns, rendering it potentially identifiable by my approach).

It is straightforward to compute historical decompositions of \( Y_m \) with respect to each of the \( k_s \) shocks in \( \epsilon_{1:M} \). However, I work with an augmented form of historical decomposition, described in Appendix C, to account for the deterministic drift introduced into historical decompositions of \( Y_m \) by standardizing \( \Delta Y_m \) to \( \Delta \tilde{Y}_m \) prior to taking principal components. Doing so allows the counterfactual paths to actually track the trajectory of \( Y_m \).

\(^2\)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.
I label the shocks based on these historical decompositions. I label $k_{mp}$ of the $k_s$ identified shocks based on a statistical labeling criterion, which I describe in detail in Appendix D. I designate as Fed Funds shocks those that shift at least the first two Fed Funds futures contracts, and especially those that move all rates. I designate as forward guidance shocks those that shift 6- through 8-quarter ED rates, (proxying for interest rate expectations near the 2-year horizon at which forward guidance was generally targeted), while moving the S&P 500 in the opposite direction, characteristic of an “Odyssean” guidance shock. 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. Allowing asset purchase shocks to potentially move Treasury yields of different maturities in opposite directions reflects the targeted nature of many such announcements and helps to distinguish such shocks from forward guidance. 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). While it is true that the differentiation between forward guidance shocks and asset purchase shocks is largely a partition of the yield curve, that is also true of the shocks identified by Swanson (2020) and RSW. However, 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 all rates), and relative to the latter I allow asset purchase shocks to impact medium-term expected rates, consistent with the signaling channel. The quantitative criterion approach described in Appendix D helps determine labels when multiple shocks match the characteristics of a single label, or vice versa.

I focus on scheduled monetary policy announcements, and include several unscheduled announcements in a robustness check. I do not consider other events like speeches, because, unlike FOMC dates, the identification assumption that movements in the common component of asset prices are related to monetary policy news is less likely to hold on such dates, when asset prices movements may not be dominated by monetary policy news. In any case, with a few exceptions, they would also likely be dwarfed by movements around FOMC meetings when aggregating to a monthly frequency shock series.

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. I characterize the historical decompositions across the full set of 104 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 report summary statistics (across announcements) of the contemporaneous response of asset prices, $Y_m$, to monetary policy shocks $\epsilon_m$, 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 in with economic theory, and thus bolster the credibility of the following analysis. I measure the contemporaneous responses to shock $j$ as $\sigma_{\Delta Y} \Lambda_{1:kmp} H_j$, where $H_j$ is the column of $H$ corresponding to the shock labeled as $j$ (Fed Funds, etc.) and $\sigma_{\Delta Y}$ is the standard deviation of $\Delta Y_m$. For interpretability, I normalize responses by 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 percentage point change in the S&P 500 for the Fed information shock. Table 1 reports the median response to each shock across all 104 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. Likewise, 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 expected 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, but also slightly increases the S&P 500. This last point is the one anomaly, but recall that these are very high-frequency relationships and longer-run dynamics can exhibit different signs. 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. Overall, even these very high-frequency relationships between asset prices and shocks accord with theory.

### 3.2 Historical decompositions

I now present historical decompositions for 12 key monetary policy announcements. These announcements match those detailed in Table 1 of Swanson (2020), 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-
Table 1: Contemporaneous responses of asset prices to high-frequency shocks

<table>
<thead>
<tr>
<th></th>
<th>FF</th>
<th>FG</th>
<th>AP</th>
<th>FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>ED8</td>
<td>0.03</td>
<td>1.00</td>
<td>0.78</td>
<td>0.69</td>
</tr>
<tr>
<td>T5</td>
<td>0.01</td>
<td>0.95</td>
<td>0.99</td>
<td>0.69</td>
</tr>
<tr>
<td>T10</td>
<td>0.03</td>
<td>0.80</td>
<td>1.00</td>
<td>0.77</td>
</tr>
<tr>
<td>SPX</td>
<td>-0.03</td>
<td>-0.39</td>
<td>0.08</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Each column reports the median across 104 announcements of $\sigma_Y A_{t+k,\eta,\nu} H_j$, where $H_j$ is the column of $H$ corresponding to the shock (if any) labeled as $j$ (Fed Funds, etc.). I normalize responses by 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 percentage point change in the S&P 500 for Fed information.

off from the ZLB. Table 4 in Appendix E.1 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 previous methodologies, the relationship is fixed over time. For each of these dates, 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 and S&P 500 returns. 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 difference 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 (2020) 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.

While the bar for significance of these movements in interest rates is subjective, I characterize the announcements that appear significant based on the measures 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 a taper), 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 equity markets to monetary policy shocks. Some significant monetary 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 somewhat more sensitive than interest rates to largely priced-in or subtle policy revisions. This heterogeneity demonstrates a strength of announcement-specific decompositions, as well as a downside of using interest rate movements alone (as in RSW) to study unconventional monetary policy shocks.

Table 2 summarizes the average relative effects of the different policy measures (across all 104 announcements), omitting the Fed Funds shock due to the small non-zero sample. I
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. 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 path is the path of the simple change from ten minutes prior to the announcement, the event study estimate. Units are percentage points.
Figure 2b: Historical decompositions of key FOMC announcements (cont’d)

See Figure 2 for notes.
Table 2: Average relative end-of-day effects

<table>
<thead>
<tr>
<th></th>
<th>3-m Treasury</th>
<th>6-m Treasury</th>
<th>2-y Treasury</th>
<th>5-y Treasury</th>
<th>10-y Treasury</th>
<th>S&amp;P 500</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\epsilon_{FG})</td>
<td>-0.06</td>
<td>-0.12</td>
<td>-0.52***</td>
<td>-0.82***</td>
<td>-0.57**</td>
<td>4.96***</td>
</tr>
<tr>
<td>(\epsilon_{AP})</td>
<td>-0.06*</td>
<td>-0.13</td>
<td>-0.36***</td>
<td>-0.95***</td>
<td>-1.05***</td>
<td>10.14***</td>
</tr>
<tr>
<td>(\epsilon_{FI})</td>
<td>0.00*</td>
<td>0.02*</td>
<td>0.05**</td>
<td>0.06***</td>
<td>0.04***</td>
<td>–</td>
</tr>
</tbody>
</table>

Regressions of the end-of-day decomposition with respect to a given shock on the decomposition of a 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 104 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.

I adjust the signs to represent an expansionary shock. As expected, forward guidance has the strongest impact on the medium-term yields, with asset purchases most strongly impacting long term yields. Both have a stimulatory effect on the S&P 500: 5 and 10% 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 yields by about 5 basis points (bp).

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. (2019) 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.

\(^3\)I omit the Fed Funds shock from this analysis due to the small non-zero sample.
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 due to 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 (2020) 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. 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 the potential of contamination by noise from other news sources. However, this concern is mitigated under my approach, since, after taking the common component of the underlying data to remove idiosyncratic noise, I also discard one or more identified “noise shocks” for many dates where $k_s > k_{mp}$.

In general, these conclusions are borne out over the remaining 92 announcements considered. Table 5 in Appendix E.1 presents summary statistics across all 104 scheduled announcements. The results confirm the conclusions noted above. 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 larger by the end of the day, although there is heterogeneity across announcements.

These results also re-affirm that the assumption of time-invariant relationships between asset prices and shocks should be avoided. Figure 7 in Appendix E.1 plots the end-of-

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4RSW consider a 2-hour window from 15 minutes prior to an announcement to 1:45 following. For a typical 2:00pm announcement, this 1:45-3:45 window is similar to my 1:50-4:01 window.
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 January 2019, 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).

### 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 contamination by noise, even though several checks are detailed above. 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 8 in the Appendix 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, as measured by Bloomberg consensus forecasts, during my sample. Thus, these are days with very large macroeconomic news shocks, but no monetary policy shocks. I estimate the model from 10 minutes prior to the relevant release until market close, as if the release were a monetary policy shock.

Table 6 in Appendix E.1 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, 5 of the 12 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. These include the only significant shock. The responses to the putative policy shocks (Fed Funds, forward guidance, and asset purchases) are very small, below 3 bp, lower than the average across all actual monetary policy announcements, and insignificant. Note that on some of these dates there were multiple major news events, and it is plausible that some combination of the news from these releases could have the profile of a monetary policy shock (driving interest rates and the S&P 500 in opposite directions). Figure 9 in the Appendix plots the full historical decompositions for each of these placebo dates. Overall, 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 news shocks. Those that are nevertheless labeled as monetary policy shocks are almost always 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 turn to conventional analysis of the effects of monetary policy, merging the responses into a timeseries of shocks. I first discuss the properties of this timeseries,
comparing it to leading alternatives. Next, I estimate the effects of the shocks on an array of financial variables. Finally, I estimate the response of macroeconomic aggregates to my shocks and investigate the features that drive differences relative to previous approaches.

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 104 announcement dates.

Figure 3 plots the timeseries, annotated with important historical events. For comparison, I plot the shock series of RSW and Swanson (2020). 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. The largest forward guidance shocks generally correspond to the most notable episodes. The most puzzling feature is some fluctuation in the asset purchase shock immediately prior to asset purchases entering the policy discourse in the fall of 2008. However, the Treasury had begun to purchase MBS at the beginning of September 2008, with some calling on the Fed to enter asset markets, in the midst of the Lehman collapse.

Broadly speaking, the shock series are similar to those estimated by Swanson (2020) and RSW. 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 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 results 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
Timeseries of the monetary policy shocks based on end-of-day historical decompositions of reference prices (blue), Swanson (2020) 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.

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 registers the aforementioned possibly surprising contractionary shock in September 2008, before the launch of QE1, which appears to a lesser extent in RSW, but is absent from the Swanson series. To ensure this anomaly does not drive results, I treat this shock as a forward guidance shock in the regressions below. All three series agree that the March 2009 QE1 announcement was the most important. 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,

5 This shock appears the day after the Lehman bankruptcy, so may represent some dimension of news that does not fit the quartet I study.
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 narratively important episodes.

4.2 Daily responses of financial variables

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

$$\Delta^h r_d = \nu + \psi \epsilon^H_d + u_d, \; d = 1, \ldots, D,$$

where $d$ indexes announcement dates, $\Delta^h r_d$ is the $h$–day change in the asset price, and $\epsilon^H_d$ is the vector of shocks described in Section 4.1, with HAC standard errors. I consider $h \in \{1, 7, 30\}$. I include the Fed Funds shock as a control, but do not report its coefficients, due to the small non-zero sample. I henceforth flip the sign of the forward guidance and asset purchase shocks, so a positive shock is expansionary, lowering the reference rate, and leave the sign of the Fed information shock unchanged, so a positive shock represents optimistic news, raising the S&P 500.

Table 3 reports the results for the full sample, with results for the ZLB period in Appendix E.2. The forward guidance shock has significant effects almost across the board at the one-day horizon. It lowers yields and raises spreads on corporate debt, increases TIPS-implied inflation expectations and lowers the VIX. At longer horizons, the effects on the Baa spread and VIX persist, while it also cause the dollar to depreciate against the Yen and Euro. The same is true during the ZLB subsample, except that the responses of corporate and TIPS spreads are more persistent. Turning to asset purchases, on impact there is a significant decrease in corporate yields, an increase in corporate spreads, and a reduction in economic policy uncertainty (EPU, Baker et al. (2016)). At longer horizons, the effect on AAA spreads reverses and there is an increase in the VIX. In the ZLB subsample, the effects on yields is persistent, and there is a stronger negative effect on both corporate spreads at longer horizons. The Fed information shock significantly increases corporate yields and lowers the VIX on impact. At longer horizons, the effect on the VIX persists, before reversing, and there are reductions in the AAA and TIPS spreads. During the ZLB subsample, there is also an increase in the TIPS spread on impact.

These results largely accord with the expected effects of the policies and the existing literature. For the ZLB period, Swanson (2020) also finds that asset purchases significantly reduce corporate yields and raise spreads on impact. He also finds a positive effect of forward

27
### Table 3: Financial market responses to monetary policy

<table>
<thead>
<tr>
<th></th>
<th>1-day change</th>
<th></th>
<th>1-week change</th>
<th></th>
<th>1-month change</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FG</td>
<td>AP</td>
<td>FI</td>
<td>FG</td>
<td>AP</td>
<td>FI</td>
</tr>
<tr>
<td>AAA yield</td>
<td>0.32**</td>
<td>1.06*</td>
<td>0.05**</td>
<td>1.03</td>
<td>0.02</td>
<td>0.16</td>
</tr>
<tr>
<td>AAA spread</td>
<td>0.42***</td>
<td>1.29***</td>
<td>0.01</td>
<td>0.41</td>
<td>0.20</td>
<td>0.06***</td>
</tr>
<tr>
<td>Baa yield</td>
<td>0.30**</td>
<td>1.30**</td>
<td>0.06**</td>
<td>0.54</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td>Baa spread</td>
<td>0.44***</td>
<td>1.05**</td>
<td>0.00</td>
<td>0.41*</td>
<td>0.76</td>
<td>0.04</td>
</tr>
<tr>
<td>TIPS spread</td>
<td>0.32***</td>
<td>0.09</td>
<td>0.02</td>
<td>0.25</td>
<td>0.67</td>
<td>0.05</td>
</tr>
<tr>
<td>JPY/USD</td>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>0.09***</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Euro/USD</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
<td>0.11***</td>
<td>0.14</td>
<td>0.01</td>
</tr>
<tr>
<td>VIX</td>
<td>0.67***</td>
<td>0.93</td>
<td>0.15***</td>
<td>0.87***</td>
<td>2.19*</td>
<td>0.12***</td>
</tr>
<tr>
<td>EPU</td>
<td>2.03</td>
<td>5.78**</td>
<td>0.03</td>
<td>0.03</td>
<td>4.84</td>
<td>0.31</td>
</tr>
</tbody>
</table>

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 2007-2019. HAC standard errors are calculated following Lazarus et al. (2018). Significant results are starred at the 10%, 5% and 1% levels.

Guidance on corporate spreads on impact; however, he estimates 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 negative at longer horizons matches the evidence for conventional policy in Gertler and Karadi (2015). Finally, the finding that forward guidance causes the dollar to depreciate is consistent with Swanson (2020) and Rogers et al. (2018).

The finding that both forward guidance and asset purchases lower various uncertainty measures mirrors results in Coenen et al. (2017). Forward guidance appears to lower the VIX, a market-based measure of expected volatility, while asset purchases lower EPU, which is a more “macro” measure, including newspaper coverage and forecast disagreement. This distinction suggests that the effects of forward guidance might be more concentrated in financial markets than those of asset purchases, as I explore in the next section. The fact that forward guidance, not asset purchases, increases implied inflation expectations is also of interest, given the widespread media coverage of inflationary risks to large-scale balance sheet expansion. Finally, the results for the Fed information shock, identified in a way that separately controls for all relevant dimensions of monetary policy, are original, and accord with theory, generally lowering uncertainty while raising interest rates.
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 (2020) 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 convert my announcement-frequency shock measures to a monthly timeseries with zeros in months without FOMC meetings, yielding 156 observations, indexed by \( r \). For a dependent variable, \( x \), I compute impulse response functions using local projections of the form

\[
x_{r+h} - x_{r-1} = \alpha h + \sum_{l=1}^{2} \pi_{l} h_{r} \epsilon_{r-l}^{HF} + \sum_{s=1}^{3} \kappa_{l} h \Delta X_{r-s} + u_{r}^{h}, h = 0, 1, \ldots, 12, \tag{9}
\]

controlling for the previous two months’ worth of the vector of monetary policy shocks (to include at least the prior meeting) and the prior quarter’s monthly macroeconomic aggregates in \( \Delta X_{r-s} \) (inflation, changes in unemployment, industrial production growth, plus S&P 500 returns and changes in the 2-year Treasury yield as additional controls). To focus on the period during which unconventional policy was most active, my baseline sample spans 2008-2017, 120 observations. The coefficient of interest is the vector \( \pi_{0} h \), the effects of month \( r \) shocks at \( r + h \). I focus on horizons up to one year, given the limited sample length, and compute HAC standard errors. I now assume constant parameters (e.g., \( \pi_{0} h \)), as does virtually the entire extant literature; doing so is necessary due to the nature of the exercise and the sample length. However, my shocks, \( \epsilon_{r}^{HF} \), were recovered without imposing similar assumptions. As above, I include Fed Funds shocks as controls, but do not report their results due to the small non-zero sample.

Figure 4 plots the dynamic responses of inflation, unemployment, and industrial production to a one standard deviation expansionary impulse to each shock, with 90% confidence intervals. The forward guidance shock does not have a significant effect on inflation. In contrast, an asset purchase shock (one that raises 10-year Treasury yields by about 3 bp) significantly increases inflation after a delay by up to about 7 bp, significant from 6-9 months.

29
Impulse responses are calculated via local projection as in equation (9) using monthly data and the sample January 2008 to December 2017 and the baseline shocks. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018).

The Fed information shock slightly decreases inflation, on the edge of significance at three horizons. Turning to unemployment, the forward guidance shock again has no significant effect. As before, the asset purchase shock has a significant effect, lowering unemployment by up to 20 bp, significant from 3 months. The Fed information shock has no significant effect. Finally, the forward guidance shock has no effect on industrial production. On the other hand, the asset purchase shock significantly raises industrial production, with an effect peaking at about 40 bp, significant from 7 months. The Fed information shock has a positive effect up to 20 bp, although it is not quite significant. The lack of effects 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. The fact that the effects of forward guidance do not extend from financial markets to the real economy was possibly foreshadowed by the earlier finding that it impacted the VIX but not the EPU index. Moreover, these findings are 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.

I explore the sensitivity of these findings; results are displayed in Appendix E.3. Extending the estimation sample to span 2007-2019 reduces the impact of the asset purchase shock on inflation, such that it becomes insignificant, while the impacts on unemployment and industrial production are essentially unchanged. The Fed information shock also significantly increases industrial production in this longer sample. Adding unscheduled announcements
increases the statistical significance of the inflation and unemployment responses to asset purchases, while reducing the effect on industrial production. Using the original statistical labeling of the asset purchase shock in September 2008 (instead of treating it as forward guidance, as discussed above) increases the precision of the estimated effects of asset purchase, while dropping it entirely has virtually no effect. I also consider shocks based on the decompositions identified using a regime-based heteroskedasticity argument described in Section 3.3. Recall that while these decompositions look quite similar to the baseline on the key dates analyzed above, that is not the case for some less prominent announcements, where the volatility changes are smaller and thus may not strongly identify the model. Nevertheless, the impulse response are consistent with the baseline, suggesting these key dates may drive results.

I have proposed an econometrically and computationally intensive approach to recovering monetary policy shocks, so it is natural to ask what has been gained relative to simpler approaches. I first use the RSW shock, which recursively residualize wide-window changes in the front Fed Funds future rate, the 4-quarter ED rate, and 10-year Treasury futures rate to recover Fed Funds, forward guidance, and asset purchase shocks (the Fed Funds shock is the change in the front future rate, the guidance shock is the residual from regressing the change in the 4-quarter rate on the Fed Funds shock, etc.). Figure 5 plots responses to these shocks, with the black dash-dot line my baseline responses. Using this simple identification approach, the effects of asset purchase shocks are stronger, but forward guidance now has puzzling significant contractionary effects on inflation (9 bp), unemployment (38 bps), and industrial production (30 bps). In Appendix E.3, I show that adding my Fed information shock series as a control changes little. I also confirm this is not a sample effect: responses to my shocks change little, with more expansionary effects for forward guidance (and Fed information), if anything. 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. Although the shock series appear similar in Figure 3, the discrepancies discussed for notable announcements impact responses.

I next consider the Swanson (2020) shocks, Figure 6. The results are very similar to those for RSW. First, the role of asset purchases broadly aligns, although the point estimates are generally larger, up to a factor of 1.5 for industrial production. Further, the forward guidance shock is again shown to have significant contractionary effects on unemployment (29 bp) and
Impulse responses are calculated via local projection as in equation (9) using monthly data, RSW’s sample January 2008 to December 2015, and shocks computed using the methodology of Rogers et al. (2018) and their replication data. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and the Swanson (2020) shocks. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

industrial production (48 bp). The Swanson responses are largely unchanged on an extended sample or adding unscheduled announcements, as reported in Appendix E.3. Including my Fed information series as a control actually produces an additional contractionary effect of guidance on inflation.

There are at least four important differences between these existing shock series and mine. Swanson uses a 30-minute window, while I consider end-of-day decompositions; RSW and Swanson do not account for the Fed information effect; I adopt a different decomposition for each announcement; and all three exploit different assumptions or properties for identification. It is easy to confirm that the choice of window length is not driving the different results; in Appendix E.3, I show that point estimates are very similar for my shocks whether
measured at 30-minute or end-of-day windows. Simply adding my Fed information series as a control in projections with the RSW or Swanson shocks does not reduce the discrepancy in responses; the same is true of subtracting it from specifications using either my 30-minute or end-of-day shocks. Thus, controlling for an information effect does not appear central, although it is still possible it may play a role earlier, in the process of recovering the shocks themselves. These findings suggest that the differences in results are likely driven by some combination of my use of announcement-specific decompositions and my use of time-varying volatility to disentangle shocks for each announcement (as opposed to RSW’s lower triangular structure or Swanson’s exclusion and narrative restrictions), which together form the novel contribution of this paper. Unfortunately, it is not easy to separate the effects of these factors, since Swanson’s assumption separating guidance and asset purchases cannot be exploited intraday, and my approach based on time-varying volatility is not straightforward to apply across announcements. However, it is possible to apply the RSW identification scheme to intraday asset price changes to identify announcement-specific decompositions. I do so, using their wide window to recover Fed Funds, forward guidance, and asset purchase shocks. Appendix E.3 shows that the resulting responses of inflation and unemployment are very similar to my baseline, but the response of industrial production to asset purchases remains larger, and that to guidance remains negative (although insignificant). These findings suggest the use of announcement-specific decompositions is central in explaining the differences in responses, although the use of identification based on volatility does play a smaller role.

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 (2002) 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, over the same period, a single shock (the asset purchase shock) has pronounced economic effects, while the others do not. 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 size shocks in a cross-country panel VAR. Their findings indicate significant stimulatory effects for the asset purchase dimension of policy, peaking around six months. The output response is about three times that of inflation, roughly according with my finding of an up to four times larger
response of industrial production.

Bundick and Smith (2020) find moderate stimulatory 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. However, their results are fairly robust to dropping key LSAP dates, but it is possible that these findings are driven by the pre-ZLB period, which dominates their sample.

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 did not have a pronounced 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. While my results are generally null, I do find that the Fed information shock has a robustly positive effect on industrial production. This effect is significant at the 90% level for several specifications.

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. 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.

On impact, both forward guidance and asset purchases lower corporate yields, raise spreads, and lower uncertainty, while at longer horizons asset purchases lower spreads and guidance causes the dollar to depreciate. Fed information shocks raise yields and lower uncertainty. Most importantly, I find substantial macroeconomic effects. Inflation, unemployment, and industrial production display significant dynamic responses to asset purchase shocks, but not to forward guidance shocks. While I obtain similar responses for asset purchases using the RSW and Swanson (2020) shocks, there are puzzling effects for forward guidance. These differences are attributable to novel features of my identification approach. 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 asset purchase policies in particular were effective with regard to a number of macroeconomic outcomes. This paper has focused on studying the particularly challenging period of the ZLB in detail. Extending the methodology backwards to assess whether forward guidance may prove more effective during more normal times presents an avenue for future work.
References


Gertler, M. and P. Karadi (2015): “Monetary policy surprises, credit costs, and eco-


A Proof of Proposition 1

Proposition 1. Under the model described by (4) and (5), $H_{d}^{\text{inf}}$, infeasibly identified from repeated samples of $\eta_{d}$, 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 $H_{d}^{\text{inf}}$ based on moments of $\eta_{d} \left(= H_{d}^{\text{inf}} \epsilon_{d} \right)$ (computed from infeasible repeated samples) must necessarily recover a unique linear mapping between $\eta_{d}$ and $\epsilon_{d}$; since $H_{d}$ provides such a mapping, it must be that $H_{d}^{\text{inf}} = H_{d}$. 

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

$$E[M_{m} \epsilon_{m}] = M \times E[\text{diag} (\sigma_{m}^{2})] = M \times \xi / M = \xi,$$

where $\xi$ is the $n \times 1$ unconditional mean of $\sigma^{2}(t)$. It is immediate that $E[M \eta_{m} \eta_{m}'] = H \xi H'$. 

Turning to the other moment used in the identification argument,

$$\text{cov} (\sigma_{m}^{2}, \sigma_{m-pM}^{2}) = \Omega_{D}^{1/2} \Diamond R^{**} (pM \times 1 / M) \Omega_{D}^{1/2}$$

where $\Omega_{D}$ is a diagonal matrix containing the diagonal of $\Omega = \text{var} (\sigma^{2}(t))$,

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

39
and 

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

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

\[ R^{**}(s+t) = R^{**}(s) + R^*(s) \, t + \frac{R(s)}{2} t^2 + o(t^2). \]

Then

\[
\begin{align*}
\Box R^{**}(p) &= \left( R^{**}(p) + R^*(p) \frac{1}{M} + \frac{R(p)}{2} \left( \frac{1}{M} \right)^2 \right) - 2R^{**}(p) \\
&\quad + \left( R^{**}(p) - R(p) \frac{1}{M} + \frac{R(p)}{2} \left( \frac{1}{M} \right)^2 \right) + o \left( \left( \frac{1}{M} \right)^2 + \left( \frac{-1}{M} \right)^2 \right) \\
&= \frac{R(p)}{2} \frac{1}{M^2} + o \left( 1/M^2 \right) \\
&= R(p)/M^2 + o \left( 1/M^2 \right).
\end{align*}
\]

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

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

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

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

where \( \zeta_m = \text{vech} \left( \eta_m \eta_m' \right) \) 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 $\frac{M}{M_1}$ spaced squared returns converges almost surely to $H\xi H'$, the mean of $\sigma^2(t)$. 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 $\text{diag}(\xi)$. In particular,

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

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

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 $\sigma_m^2$, $\epsilon_m$ is random normal with variance $\sigma_m^2$. 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,

$$
\frac{1}{M} \sum_{m=1}^{M} M \epsilon_m \epsilon_m' \xrightarrow{a.s.} \text{diag} \left( \xi \right) + 0 = \text{diag} \left( \xi \right).
$$

Therefore,

$$
\frac{1}{M} \sum_{m=1}^{M} M \eta_m \eta_m' \xrightarrow{a.s.} H \text{diag} \left( \xi \right) H'.
$$

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

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

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

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

The first of these summands can be further decomposed as

$$
M^2 E \left[ \text{vec} (\epsilon_m \epsilon_m') \text{vec} (\epsilon_{m-pM} \epsilon_{m-pM}') \right] = M^2 GE \left[ \sigma_m^2 \sigma_{m-pM}^2 \right] G' \otimes \left( \text{vec} \left( E \left[ z_m z_m' \right] \right) \text{vec} \left( E \left[ z_{m-pM} z_{m-pM}' \right] \right) \right)
$$

$$
= M^2 GE \left[ \sigma_m^2 \sigma_{m-pM}^2 \right] G' \otimes \left( v_n v_n' \right)
$$

$$
= M^2 GE \left[ \sigma_m^2 \sigma_{m-pM}^2 \right] G' = G \text{cov} \left( M \sigma_m^2, M \sigma_{m-pM}^2 \right) G' + G \xi' \xi' G',
$$

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

$$
\frac{1}{M} \sum_{m=pM+1}^{M} M^2 \text{vec} (\epsilon_m \epsilon_m') \text{vec} (\epsilon_{m-pM} \epsilon_{m-pM}') \quad \xrightarrow{a.s.} \quad \lim_{M \to \infty} G \text{cov} \left( M \sigma_m^2, M \sigma_{m-pM}^2 \right) G' + G \xi' \xi' G' + 0
$$

$$
= G \Omega^{1/2} R (p) \Omega^{1/2} G' + G \xi' \xi' G'.
$$

In particular, taking fourth moments of the integral yielding $\sigma_m^2$ and recognizing that the entries of $R (t)$ are bounded by $\pm 1$ delivers the result.
Finally,

\[
\frac{1}{M} \sum_{m=pM+1}^{M} M^2 \text{vec} \left( \epsilon_m \epsilon'_m \right) \text{vec} \left( \epsilon_{m-pM} \epsilon'_{m-pM} \right)' - \left( \frac{1}{M} \sum_{m=1}^{M} M \text{vec} \left( \epsilon_m \epsilon'_m \right) \right)' \left( \frac{1}{M} \sum_{m=1}^{M} M \text{vec} \left( \epsilon_m \epsilon'_m \right) \right)'
\]

\[
\xrightarrow{a.s.} G \Omega_D^{1/2} R (p) \Omega_D^{1/2} G' + G \xi \xi' G' - G \xi \xi' G'
\]

\[
= G \Omega_D^{1/2} R (p) \Omega_D^{1/2} G'.
\]

This immediately implies that

\[
\frac{1}{M} \sum_{m=pM+1}^{M} M^2 \zeta_m \zeta'_{m-pM} - \left( \frac{1}{M} \sum_{m=1}^{M} M \zeta_m \right) \left( \frac{1}{M} \sum_{m=1}^{M} \zeta_m \right)'
\]

\[
\xrightarrow{a.s.} L (H \otimes H) G \left( \Omega_D^{1/2} R (p) \Omega_D^{1/2} \right) G' (H \otimes H)' L',
\]

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, \( \epsilon_j \). In particular, let the impulse response matrix of \( F_m \) to \( \epsilon_m \) at horizon \( h \) be \( \phi_h \). Then the historical decomposition of \( F_m \) with respect to \( \epsilon_j \) is \( \sum_{h=0}^{m} \phi_h t_j \epsilon_{m-h} \), where \( t_j \) 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 \( \Lambda \sum_{h=0}^{m} \phi_h t_j \epsilon_{m-h} \). Finally, rescaling by \( \sigma_{\Delta Y} \) (standard deviation of \( \Delta Y_m \)) and cumulating the decomposition gives the value for the data in levels, \( Y_m \),

\[
\Psi_{jm} = \sum_{s=1}^{m} \sigma_{\Delta Y} \Lambda \sum_{h=0}^{s} \phi_h t_j \epsilon_{s-h}.
\]

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, \( Y_m \).\(^7\) First differences \( \Delta Y_m \) 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 \( \Delta Y_m \). When summing across \( m \) to compute \( \Psi_{jm} \), cumulating \( \Delta \tilde{Y}_m \) responses introduces a mechanical \(-\mu m \) “wedge”, where \( \mu \) is the mean of \( \Delta Y_m \) (which was subtracted to compute \( \Delta \tilde{Y}_m \)), between \( \Psi_{jm} \) and \( Y_m \). This wedge implies a mechanical drift towards zero, since

\(^7\)More precisely, I refer to summing to the common component of the path of \( Y_m \), since the exact path of a given variable, \( Y_{im} \), will not be traced out by the first \( n \leq 4 \) principal components of \( Y_m \), regardless of what transformations are adopted prior to computation.
\[ \sum_{m=1}^{M} \Delta \tilde{Y}_m = 0. \] 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 aggregate, 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 common component and that shocks on which \( Y_m \) places zero weight (through \( \Lambda \), \( H \), or both) should have a decomposition value of zero. Simply adding \( \mu m \) back in to all \( \Psi_{jm} \) would violate both of these conditions. Instead, I add a total of \( \mu m \) across all shocks \( j \), adding \( w_{ijm} \mu m \) to each decomposition \( \Psi_{ijm} \), where \( w_{ijm} = |\Psi_{ij(m-1)}| / \sum_{l=1}^{k_s} |\Psi_{il(m-1)}| \). 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 \( Y_m \).

D Details on shock labeling

Having estimated the \( k_s \) identifiable shocks, it remains to label the \( k_{mp} \) monetary policy shocks. I do so based on the augmented historical decompositions of the 20 data series with respect to the \( k_s \) identifiable shocks. Let \( A_{ij} = M^{-1} \sum_{m=1}^{M} \Psi_{ijm} \) be the area under the 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 area under 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,

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

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 \( \Theta \) and \( S \) to 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,

\[
C_{FF,j} (S_{j}, \Theta_{j}) = \begin{cases} 
1 & \text{if } \forall i \neq \text{SPX}, \Theta_{ij} > 2/3 \\
\frac{1}{2} \sum_{i \in \{FF1, FF2\}} \Theta_{ij} & \text{otherwise.}
\end{cases}
\]

In the first case, if shock \( j \) explains over 2/3 of movements in all interest rate series, \( C_{FF,j} \)
is set to its maximum value to strongly favour labeling as the Fed Funds shock; otherwise, $C_{FF,j}$ is the average of $\Theta_{ij}$ over the two first Fed Funds futures contracts.

For the forward guidance shock,

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

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 its 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 $\Theta_{ij}$ 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 $\Theta_{ij}$. Then,

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

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 $\Theta_{ij}$ over $s_T$ and the S&P 500, and otherwise is equal to zero.

For the Fed information shock,

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

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 $\Theta_{ij}$ over all long rates and the S&P 500, and otherwise equal to zero.

Having computed $C(S, \Theta)$, I search for the combination of $k_m$ shocks and labels for which the sum of the corresponding elements of $C$ is maximized, under two additional restrictions. First, if the front Fed Funds future rate varies by less than a basis point, I restrict there to
be no Fed Funds shock. Second, 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 $\Theta_{SPXj}$ with zero when computing $C_{FG,j}$ and $C_{AP,j}$ (penalizing for the fact that the movement of equities is in the wrong direction for those shocks) and replaces $\Theta_{ij}$ 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 however many shocks remain using this modified criterion.

E Additional empirical results

This section reports additional empirical results covering the announcement-specific decompositions and the responses of financial variables and macroeconomic aggregates to the time-series of shocks.

E.1 Announcement-specific decompositions

In this section I report details of key announcement dates, provide additional summary of the decompositions across announcements, and present sensitivity analysis of the decompositions for key announcement dates.

Table 4 reports details of the content of the 12 key announcements covered in detail in the text. It is largely copied from Swanson (2020), with 2 announcements added.

Table 5 reports summary statistics across the full set of 104 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 ($\delta Y_i$) 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 comparable whether the 30-minute or 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

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8If the announcement date is within 5 business days of the expiry of the front contract, I consider the next month’s contract instead. I make an exception to the “no Fed Funds shock” restriction for two announcements, for which $k_{mp} = 4$, despite only very small movements in short Fed Funds futures.
“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). This exercise shows that in general there are few significant shocks, even during this period of novel monetary policy.

Figure 7 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 8 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 key 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 9 plots historical decompositions for 10 placebo dates. These dates are chosen to correspond to the 10 largest macroeconomic release surprises (measured using Bloomberg consensus forecasts) during the sample. This poses a stern test, as these are certainly major news events, which may impact interest rates and equities, but 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. 5 of the 12 identified shocks across the 10 days are labeled as Fed information shocks. No other shock has a significant effect on its reference price.

E.2 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 (2020), 2009-2015. The results largely accord with those for the full sample, as noted in the text.
Table 4: Key FOMC announcements 2008-2015

<table>
<thead>
<tr>
<th>Month</th>
<th>Announcement</th>
</tr>
</thead>
<tbody>
<tr>
<td>December 2008</td>
<td>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</td>
</tr>
<tr>
<td>March 2009</td>
<td>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”)</td>
</tr>
<tr>
<td>November 2010</td>
<td>FOMC announces it will purchase an additional $600B of longer-term Treasuries (a.k.a. “QE2”)</td>
</tr>
<tr>
<td>August 2011</td>
<td>FOMC announces it expects to keep the federal funds rate between 0 and 25 bp “at least through mid-2013”</td>
</tr>
<tr>
<td>September 2011</td>
<td>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”)</td>
</tr>
<tr>
<td>January 2012</td>
<td>FOMC announces it expects to keep the federal funds rate between 0 and 25 bp “at least through late 2014”</td>
</tr>
<tr>
<td>September 2012</td>
<td>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</td>
</tr>
<tr>
<td>December 2012</td>
<td>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</td>
</tr>
<tr>
<td>September 2013</td>
<td>FOMC announces that it will wait to taper asset purchases</td>
</tr>
<tr>
<td>December 2013</td>
<td>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</td>
</tr>
<tr>
<td>December 2014</td>
<td>FOMC announces that “it can be patient in beginning to normalize the stance of monetary policy”</td>
</tr>
<tr>
<td>March 2015</td>
<td>FOMC announces that “an increase in the target range for the federal funds rate remains unlikely at the April FOMC meeting”</td>
</tr>
</tbody>
</table>

This table is replicated from Swanson (2020), with the addition of details on the December 2008 and September 2013 announcements.

Figure 7: 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.
Table 5: Summary statistics for historical decompositions

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<th>1.96 s.d.</th>
<th>2.58 s.d.</th>
<th>mean</th>
<th>median</th>
<th>1.96 s.d.</th>
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<td>$</td>
<td>\delta Y_i</td>
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<td>$</td>
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<td>0.01</td>
<td>3</td>
</tr>
<tr>
<td>T10, FG</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>10</td>
<td>5</td>
<td>0.04</td>
<td>0.03</td>
<td>11</td>
</tr>
<tr>
<td>T10, AP</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>3</td>
<td>2</td>
<td>0.02</td>
<td>0.01</td>
<td>5</td>
</tr>
<tr>
<td>T10, FI</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>2</td>
<td>1</td>
<td>0.02</td>
<td>0.01</td>
<td>5</td>
</tr>
<tr>
<td>SPX, FF</td>
<td>0.20</td>
<td>0.07</td>
<td>0.26</td>
<td>3</td>
<td>3</td>
<td>0.12</td>
<td>0.12</td>
<td>3</td>
</tr>
<tr>
<td>SPX, FG</td>
<td>0.20</td>
<td>0.12</td>
<td>0.29</td>
<td>4</td>
<td>2</td>
<td>0.68</td>
<td>0.41</td>
<td>11</td>
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<tr>
<td>SPX, AP</td>
<td>0.14</td>
<td>0.09</td>
<td>0.26</td>
<td>1</td>
<td>1</td>
<td>0.11</td>
<td>0.11</td>
<td>4</td>
</tr>
<tr>
<td>SPX, FI</td>
<td>0.37</td>
<td>0.24</td>
<td>0.22</td>
<td>0</td>
<td>0</td>
<td>0.11</td>
<td>0.11</td>
<td>5</td>
</tr>
</tbody>
</table>

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 4:01 pm. 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 8: 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 path is the path of the simple change from ten minutes prior to the announcement, the event study estimate. Units are percentage points.
Figure 8b: Historical decompositions of key FOMC announcements: regime approach (cont’d)

See Figure 8 for notes.
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 release surprises from 2007-2019 (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 path 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

<table>
<thead>
<tr>
<th>Date</th>
<th>FG</th>
<th>FF</th>
<th>ED8, FG</th>
<th>T10, AP</th>
<th>SPX, FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>7/16/09</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.03</td>
</tr>
<tr>
<td>1/31/13</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>12/11/08</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.02</td>
</tr>
<tr>
<td>12/31/08</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>6/27/08</td>
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<td>0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>7/13/17</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>10/16/08</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>12/10/09</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>1/8/09</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>8/24/10</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
</tbody>
</table>

End-of-day responses computed using historical decompositions following the baseline model for placebo dates corresponding to the 10 largest macroeconomic release surprises (based on Bloomberg consensus forecasts) from 2007-2019. Results are starred based on economic significance, corresponding to 1.96 and 2.58 times the average standard deviation of the relevant asset prices in the hours following monetary policy announcements.

Table 7: Financial market responses to monetary policy

<table>
<thead>
<tr>
<th></th>
<th>1-day change</th>
<th>1-week change</th>
<th>1-month change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FG</td>
<td>AP</td>
<td>FI</td>
</tr>
<tr>
<td>AAA yield</td>
<td>-0.44**</td>
<td>-1.02*</td>
<td>0.05</td>
</tr>
<tr>
<td>AAA spread</td>
<td>0.52***</td>
<td>1.02***</td>
<td>0.00</td>
</tr>
<tr>
<td>Baa yield</td>
<td>-0.38*</td>
<td>-1.31*</td>
<td>0.07*</td>
</tr>
<tr>
<td>Baa spread</td>
<td>0.58***</td>
<td>0.72</td>
<td>0.02</td>
</tr>
<tr>
<td>TIPS spread</td>
<td>0.23**</td>
<td>0.23</td>
<td>0.06**</td>
</tr>
<tr>
<td>JPY/USD</td>
<td>-0.01</td>
<td>-0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Euro/USD</td>
<td>-0.01**</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>VIX</td>
<td>-0.53*</td>
<td>0.60</td>
<td>-0.16***</td>
</tr>
<tr>
<td>EPU</td>
<td>1.52</td>
<td>-7.11**</td>
<td>-0.05</td>
</tr>
</tbody>
</table>

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 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.
E.3 Alternative impulse responses

In this section, I present sensitivity analysis for the baseline impulse responses of macroeconomic aggregates, as well as results under alternative identification schemes.

Figure 10 plots responses using a sample running the length of my full timeseries of shocks, 2007-2019.

Figure 11 augments the sample with five unscheduled announcements, constituting the four over this time period considered by Swanson (2020), plus one in October 2019. For months with unscheduled announcements, I take the simple sum of shocks across those announcements.

Figure 12 uses the original statistical labeling of a large September 2008 asset purchase shock, even though asset purchase policies did not begin until the next FOMC cycle. As discussed in the text, the Treasury had begun MBS purchases at this time, and some had begun to call for the Fed to do the same. There are also asset purchase shocks during early 2008 in the Swanson (2020) timeseries. Treating the shock instead as a forward guidance shock leaves the responses largely unchanged from the baseline in Figure 4.

Figure 13 considers shocks recovered using the alternative Rigobon (2003) regime-based identification scheme described in Section 3.3. I fix the number of identifiable shocks to be the same as under the baseline. However, for the majority of announcement dates, the Lütkepohl et al. (2020) test suggests that there is not adequate variation across regimes to fully identify the model, so the shock measures may be unreliable. This issue illustrates the value of using identification based on time-varying volatility instead, using the continuous variation in volatilities, as opposed to discrete variance regimes.

Figure 14 uses shocks computed using the Rogers et al. (2018) methodology and replication data, with my Fed information shock added as control.

Figure 14 uses my baseline shocks with the sample restricted to January 2008 to December 2015, to match the sample end date for the Rogers et al. (2018) shocks.

Figure 16 uses the Swanson (2020) shocks for an extended sample, January 2007 to June 2019. Figure 17 adds the unscheduled announcements from Swanson’s sample. Figure 18 adds my Fed information shock to the Swanson shocks as a control.

Figure 19 measures shocks using my methodology but the conventional 30-minute window. Figure 20 uses the same shocks, but omits the Fed information series.

Figure 21 applies the Rogers et al. (2018) identification approach to intraday asset price movements in an attempt to disentangle the effects of using announcement-specific decompositions from my volatility-based identification argument. In particular, I take minute-by-minute changes in the front Fed Funds future rate over the Rogers et al. (2018) 2-hour window as the intraday path of the Fed Funds shock; the residual in the regression of changes...
Impulse responses are calculated via local projection as in equation (9) using monthly data and the sample January 2007 to December 2019. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

in the 8-quarter ED rate on the Fed Funds shock is the forward guidance shock; and the residual in the regression of changes in the 10-year Treasury yield on the Fed Funds and forward guidance shocks is the asset purchase shock. The daily shock measure is the sum of these intraday shock series over the 2-hour window.
Figure 11: Dynamic response of macroeconomic aggregates: unscheduled announcements

Impulse responses are calculated via local projection as in equation (9) using monthly data and the sample January 2008 to December 2017, including unscheduled announcements. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

Figure 12: Dynamic response of macroeconomic aggregates: no September 2008 AP shock

Impulse responses are calculated via local projection as in equation (9) using monthly data and the sample January 2008 to December 2017, setting the September 2008 asset purchase shock to zero. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.
Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and shocks identified using the Rigobon (2003) regime-based approach. Responses are scaled to a one standard deviation expansionary impulse for each shock. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2015, and shocks computed using the methodology of Rogers et al. (2018) and their replication data, augmented with a Fed information shock. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.
Figure 15: Dynamic response of macroeconomic aggregates: Rogers et al. (2018) sample

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2015, and my baseline shocks. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

Figure 16: Dynamic response of macroeconomic aggregates: Swanson shocks with extended sample

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2007 to June 2019, and the Swanson (2020) shocks. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.
Figure 17: Dynamic response of macroeconomic aggregates: Swanson shocks with unscheduled announcements

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and the Swanson (2020) shocks including unscheduled announcements. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

Figure 18: Dynamic response of macroeconomic aggregates: Swanson shocks with Fed information

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and the Swanson (2020) shocks augmented with a Fed information shock. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.
Figure 19: Dynamic response of macroeconomic aggregates: 30-minute shocks

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and shocks based on the 30-minute historical decompositions. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.

Figure 20: Dynamic response of macroeconomic aggregates: 30-minute shocks omitting Fed information

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and shocks based on the 30-minute historical decompositions, omitting the Fed information shock. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.
Figure 21: Dynamic response of macroeconomic aggregates: intraday Rogers et al. (2018) identification

Impulse responses are calculated via local projection as in equation (9) using monthly data, the sample January 2008 to December 2017, and shocks computed applying the Rogers et al. (2018) recursive identification approach to minute-by-minute asset price changes over their 2-hour window for each announcement. Responses are scaled to a one standard deviation expansionary impulse. 90% HAC confidence intervals are calculated following Lazarus et al. (2018). The dash-dot line is the baseline response.