Monetary Policy News and Systemic Risk at the Zero Lower Bound [*]

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Abstract

This paper employs a recent contribution to the construction of the shadow nominal interest rate during the zero lower bound episode and Greenbook forecasts to obtain a measure of monetary policy shocks over that time period. It then identifies monetary policy news shocks as a novel measure of the forward-looking conduct of monetary policy in the U.S. Using the data from 1987—2010, it shows that neither monetary news nor surprises affected alternative measures of systemic risk over the full sample. However, monetary news shocks announcing future reductions in interest rates were effective in lowering most (but not all) systemic risk measures during the zero lower bound period, unlike monetary surprises.

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Keywords: Monetary policy; news shocks; systemic risk; zero lower bound; Greenbook forecasts.

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1 Introduction

Interest in the effect of monetary aggregates on the macroeconomy has a deep intellectual tradition in economics and political philosophy.[1] Modern interest in the transmission of monetary policy started with the seminal work of Friedman and Schwartz (1971), leading to a wide gamut of approaches to the subject. Over the past five decades, the profession has gradually settled on identifying exogenous variation in the conduct of monetary policy primarily by means of modeling central bank reaction functions where the monetary policy tool, such as the nominal short-term interest rate, is set in response to the underlying macroeconomic conditions. Sims (1980) provided an early, seminal methodological contribution that places such a reaction function within a multivariate, vector autoregressive (VAR) framework. Taylor (1991) proposed a popular description of a parsimonious specification of such a reaction function that has since been dubbed the 'Taylor rule'. Christiano et al. (1999) provide a comprehensive overview of the identification of monetary policy shocks primarily using least squares and narrative methods, whereas Fernandez-Villaverde (2010) offers a broad overview of maximum likelihood methods with an emphasis on the Bayesian estimation of dynamic stochastic general equilibrium (DSGE) models that have gained in popularity since the early 2000s. By the mid-2000s, the profession has reached a broad consensus in terms of monetary policy reaction functions responding to macroeconomic aggregates, such as inflation and real activity, and focusing on the transmission of monetary policy shocks to these aggregates as means of evaluating its effectiveness.

The Great Recession of 2008-2009 challenged the standard analysis on at least two dimensions. First, its severity resulted in the federal funds rate (FFR)—the short-term interest rate in the interbank market that the Federal Reserve has used as the primary policy tool—reaching its zero lower bound (ZLB) and rendering the standard conduct of monetary policy ineffective and stimulating acute professional interest in the unconventional conduct of monetary policy.[2] One important example of the latter is the so-called "forward guidance" whereby the central bank, while unable to change the current interest rate, sends signals to the economic agents about its future conduct of

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[1]For a brief historical overview of this tradition, see Fernandez-Villaverde (2010).

[2]Krugman (1998) is widely credited with resurrecting the treatment of the zero lower bound by placing the old Keynesian concern with the liquidity trap in the context of a highly stylized microfounded model. Eggertsson and Woodford (2003) were first to analyze the effect of the ZLB in the context of the standard New Keynesian DSGE model.

policy, thereby affecting current outcomes via agents' forward-looking expectations. Second, the concern with financial stability has taken center stage in both policy and academic circles, leading to proposals for the Federal Reserve to add it as a third objective to its dual mandate of stable prices and full employment.[3] Therefore, the central bank's ability to improve financial stability, particularly under severely recessionary conditions that impose limitations on the conventional conduct of monetary policy, is likely to be of paramount importance in the next crisis.

The present paper addresses both of these concerns by extending the recent literature on the transmission of forward-looking monetary policy at the ZLB. It begins by constructing monetary policy surprise shocks using the Federal Reserve's real-time forecasts of real activity and inflation following the framework developed by Romer and Romer (2004). Since the FFR reached the ZLB during the Great Recession, I use the shadow rate series constructed by Wu and Xia (2016) who employ a nonlinear term structure model to develop a measure of the implied short-term interest rate given the rest of the yield curve at the ZLB. I then use a technique developed by Barsky and Sims (2011) to identify monetary news shocks as the weighted average of reduced-form residuals in a vector autoregressive (VAR) model for variables other than monetary news. My approach closely follows that of Ben Zeev et al (2016) with several important distinctions: monetary shocks are defined using the Romer and Romer (2004) approach and not as deviations from an *ad hoc* Taylor rule; monetary news shocks are derived in the VAR model estimated at the monthly frequency; the sample is extended into the Great Recession using the Wu-Xia shadow rate. Finally, I investigate the effect of both monetary surprises and news on measures of systemic risk summarized in Giglio et al (2016) using Jorda's (2005) method of local projections in a single-equation framework. The resulting impulse responses demonstrate that while monetary surprises have no effect on alternative measures of systemic risk before or during the ZLB, monetary news shocks, while also ineffective in normal times, have a strong and statistically significant effect at the zero lower bound. These results suggest that forward-looking monetary policy can be a powerful tool in mitigating systemic risk under severely adverse conditions.

The rest of the paper is organized is follows. Section 2 describes the data used in this paper's empirical exercises. Section 3 details the construction of monetary policy surprise shocks before

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[3]For overviews of the recent academic literature on the role of financial stability concerns in the conduct of monetary policy, see Smets (2014) and Adrian and Liang (2016). For policy-makers' views on the tradeoffs involved in aiming monetary policy to achieve financial stability, see Fisher (2016) and Powell (2017).

and during the ZLB episode. Section 4 describes the Barsky-Sims (2011) news shock identification procedure and derives a measure of monetary policy news shocks. Section 5 uses the method of impulse responses by local projections to study the effect of monetary news and surprises on measures of systemic risk before and during the zero lower bound. It finds that monetary policy surprises had no effect on measures of systemic risk before and during the Great Recession, whereas monetary news significantly reduced systemic risk. Finally, Section 6 offers concluding remarks.

2 Data

The data for the empirical exercises in the present paper cover (with minor exceptions noted below) the period from August 1987 through December 2010 and come from several sources. Monetary surprise shocks are constructed using the methodology that closely follows Romer and Romer (2004) and uses the series for the estimates of output gap, unemployment rate, real output growth rate, GDP/GNP deflator and core CPI inflation. The Greenbook Financial Assumptions projections for the current federal funds rate (FFR) target are available only through the September 2008 Federal Open Market Committee (FOMC) meeting, thus ending early in the Great Recession, just as the conduct of monetary policy began to shift towards unconventional monetary policy. To extend the target FFR series through December 2010, I use the monthly shadow nominal interest rate series developed by Wu and Xia (2016) rounded to the nearest 25 basis points, since the Greenbook FFR projections are given in 25-basis-point increments. Figure 1 provides a comparison of the historical current-quarter (zero-horizon) FFR target and the Wu-Xia (2016) rate, offering visual evidence of a smooth transition between the two in 2006—2008. Estimates of monetary surprise shocks below use the zero-horizon FFR projections through September 2008 and the rounded Wu-Xia (2016) rate for October 2008 through December 2010.

Estimates of monetary news shocks require additional macroeconomic data. These are monthly data for August 1987 through December 2010 comprising the seasonally adjusted civilian unemployment rate, consumer price index, TED spread, slope of the yield curve calculated as the difference between the yields on a 10-year Treasury and the 3-month T-bill are from the FRED2 database maintained by the Federal Reserve Bank of St. Louis. Together with the Wu-Xia (2016) rate, innovations in these series will be used to identify monetary news shocks.
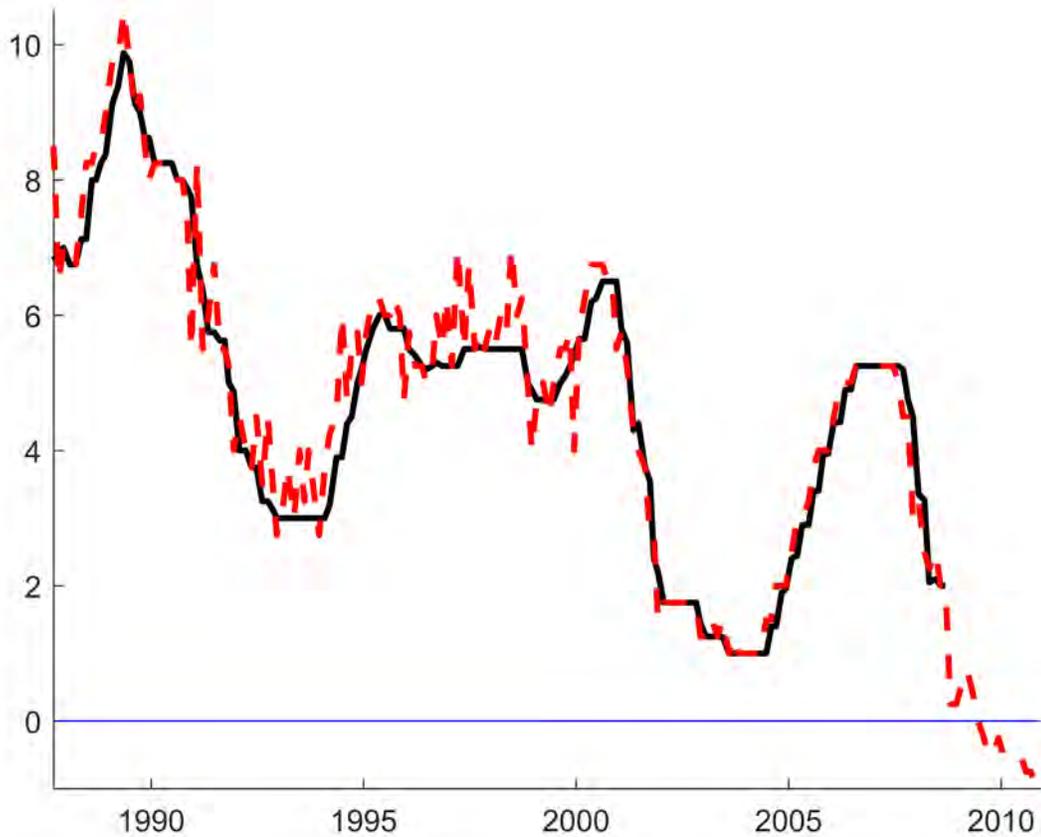
Figure 1: Greenbook zero-horizon federal funds rate target (solid black line) and the Wu-Xia shadow interest interest rate (dashed red line) rounded to the nearest 25 basis points.

Finally, since the primary purpose of this paper is to evaluate the transmission of monetary surprise and news shocks to measures of systemic risk, I use a large number of systemic risk measures proposed in the recent literature. Giglio et al (2016) have studied the transmission of shocks to several such measures to real activity, organized into the following broad categories:

- *Institution-specific risk*: Conditional Value at Risk (CoVaR) and ΔCoVaR from Adrian and Bunnermeier (2016); marginal expected shortfall (MES) from Acharya et al (2016) and its modification, MES-BE, due to Brownlees and Engle (2016);

- *Comovement and contagion*: Absorption Ratio and its change due to Kritzman et al (2011) given by the fraction of the variance of stock returns of 51 US industries explained by the first $K = 3$ principal components; dynamic causality index (DCI) from Billio et al (2012)

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which is given by the number of significant Granger-causality relationships in banks' equity returns; and the international spillover index (ISI) of Diebold and Yilmaz (2009) that measures international comovement in macroeconomic variables.[4]

- *Volatility and instability*: Giglio et al (2016) construct "Volatility" as the average equity volatility of the largest 20 financial institutions; "Turbulence" due to Kritzman and Li (2010) is a measure of recent equity returns' covariance relative to a longer-term covariance; CatFin, a financial firms' VaR measure developed by Allen et al (2012); Giglio et al (2016) measures of 20 largest financial institutions' measures of book leverage and market leverage, as well as their Herfindal index for financial company equity concentrations.

- *Liquidity and credit*: Amihud's (2002) illiquidity measure (AIM); TED spread; default spread; the Gilchrist and Zakrajsek (2012) credit spread; and the term spread.[5]

- *Index of indexes*: Partial Quantile Regression (PQR) of Giglio et al (2016) that extracts the principal components from the above 19 measures and uses them in predictive quantile regressions for forecasting real activity. Increases in all of the above 19 measures correspond to heightened systemic risk, whereas *lower* values of PQR associated with reductions in real activity signal elevated systemic risk.

Since the Federal Reserve provided a monetary stimulus using measures other than the FFR, inclusion of some of the variables from the "liquidity and credit" category seems warranted to reflect the forward-looking nature of the conduct of unconventional monetary policy during the Great Recession and to disentangle the differences between monetary policy shocks and credit market disruption. A more detailed discussion of this process follows in Section 4.

3   Monetary Policy Shocks Before and During the Zero Lower Bound

Traditionally, monetary policy surprises have been defined as residuals from a structural feedback equation for the nominal interest, such as the Taylor rule, or from a reduced-form specification

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[4]The ISI series end in April 2010.
[5]The Gilchrist and Zakrajsek (2012) credit spread series end in September 2010.

that includes lags of the nominal interest late and other macroeconomic variables, as would be the case in the vector autoregressive (VAR) framework, estimated on the final vintage of the macroeconomic data. Romer and Romer (2004), however, argued that the information available to the Federal Reserve in real-time on forecasts of future inflation and real-activity is more relevant for the definition of monetary shocks, since it better reflects both the state of the central bank's knowledge of the underlying conditions and the forward-looking conduct of monetary policy. The specification identifying the parameters of the interest-setting rule then can be given by:

$$\Delta ff_m = \alpha + \beta ff_{m-1} + \sum_{i=-1}^{H} \gamma_i y_{m,i} + \sum_{i=-1}^{H} \lambda_i (y_{m,i} - y_{m-1,i}) + \sum_{i=-1}^{H} \varphi_i \pi_{m,i} + \sum_{i=-1}^{H} \theta_i (\pi_{m,i} - \pi_{m-1,i}) + \rho' \mathbf{X_m} + \epsilon_m,$$

(1)

where Δff_m is the change in the intended FFR around the FOMC meeting m, y_m is the forecast of a measure of real activity, $(y_{m,i} - y_{m-1,i})$ are revisions in forecasts of real activity, π_m is the forecast of inflation, $(\pi_{m,i} - \pi_{m-1,i})$ are revisions in inflationary forecasts, $\mathbf{X_m}$ is the vector of additional controls, and ϵ_m is the monetary policy surprise. Romer and Romer (2004) used the current-quarter estimate of the unemployment rate for $\mathbf{X_m}$, while Bluedorn et al. (2017) augmented (1) with forecasts and revisions in the capacity utilization rate. Romer and Romer (2004) employed the maximum forecast horizon of $H = 2$; however, since the sample in this paper starts later than theirs and longer forecasts are available, I set $H = 4$. Romer and Romer (2004) used the GNP/GDP growth rate for a measure of real activity and the percentage change in the corresponding deflator for inflation. However, the Greenbook forecasts also include output gap and the unemployment rate change for real activity and core CPI growth for inflation. Without taking a position on the relevant macroeconomic variables that should enter the specification for (1), I do not include additional controls in $\mathbf{X_m}$ but estimate that equation using all possible combination of the three measures of real activity and the two measures of inflation and take the average of the resulting monetary policy surprises. Figure 2 plots the average shock series against the residuals from individual specifications estimated for August 1987 through September 2008, i.e. without relying on the Wu-Xia (2016) series, and shows that all specifications delivery nearly identical series for the monetary policy shocks.

Another issue concerns the switch to the Wu-Xia shadow rate to model monetary surprises at the zero lower bound. To see whether adding these series through December 2012 materially
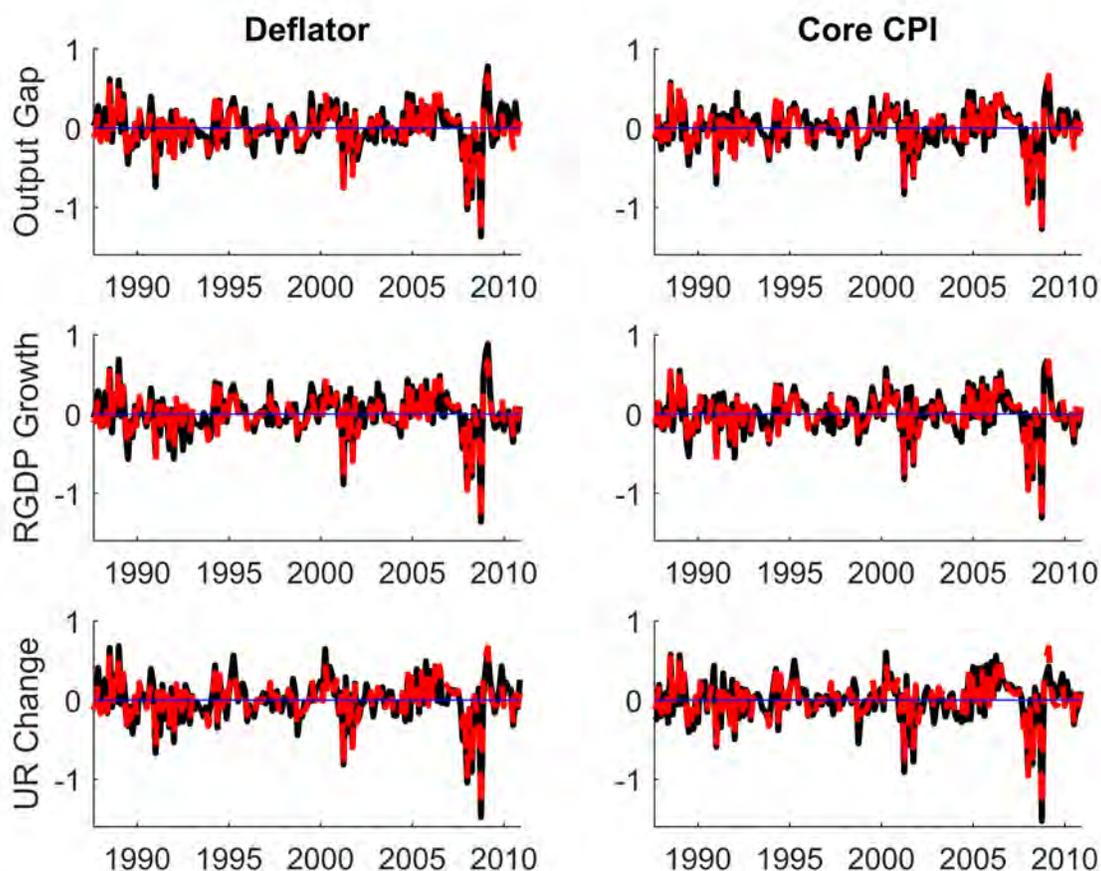
Figure 2: Monetary policy surprises from individual combinations of measures of inflation and real activity (dashed red line) vs. average across all six specifications (black solid line).

affects the estimates of monetary surprises, I estimate (1) through September 2008 using the FFR target series as the monetary policy instrument and then re-estimate it for the full sample through December 2010, appending the Wu-Xia (2016) series rounded to the nearest 25 basis points to the FFR target starting in October 2010. Figure 3 plots the average measure of monetary policy surprises estimated through September 2008 from Figure 2 against the corresponding measure with the Wu-Xia (2016) series at the end of the sample. While there are some differences in the monetary policy surprises before the Great Recession, they appear to be negligible. Both measures identify large negative surprises of about -90 basis points early in 2008 and the extended series points to another round of easing in 2009 of about -140 basis points. The large positive surprise of about 60 basis points close to the end of the sample corresponds to the end of the Federal Reserve's first round of quantitative easing (QE1) in March 2010. The monetary surprise series, therefore, appears

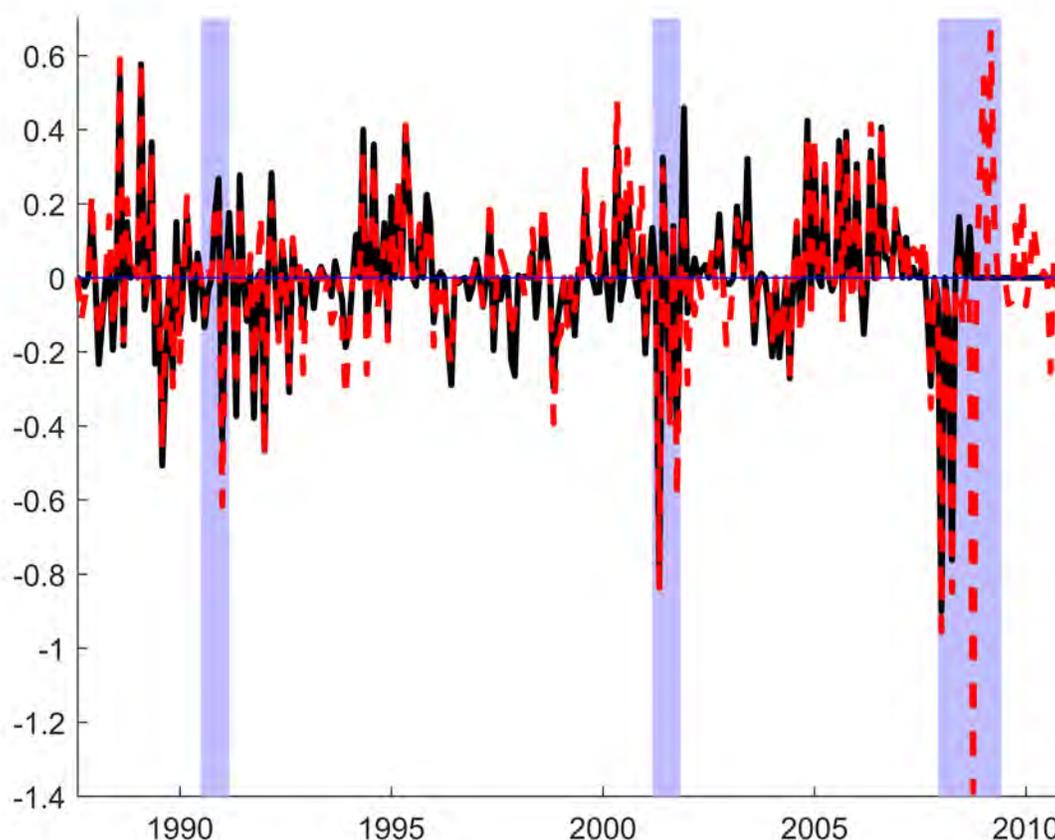to capture the main features of the monetary policy conduct during the Great Recession quite well.

Figure 3: Monetary policy surprises using Wu-Xia (2016) series for 2008-2010 (dashed red line) vs. the surprises estimated on actual Greenbook FFR through September 2008 (black solid line). (Shaded areas are the recessions defined by the National Bureau for Economic Analysis (NBER).

4   Barsky and Sims (2011) Identification Procedure and A Measure of Monetary News

The exercise of identifying monetary news shocks carried out below follows the recent methodological contribution of Barsky and Sims (2011) who proposed identifying technological news shocks in the context of a VAR model with the total-factor productivity (TFP) series and other, particularly forward-looking, macroeconomic variables.[6] News shock series is defined as as the weighted average

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[6]Alternatively, news shocks can be identified from a structural DSGE model. See Schmitt-Grohe and Uribe (2012) for an application to TFP news or Milani and Treadwell (2012) and Best and Kapinos (2016) for applications to

of reduced-form residuals *on all variables other than* the TFP series, which, as Kurmann and Otrok (2013) emphasize, may be considered exogenous to the other macroeconomic variables in the VAR model. The weights on these residuals are selected so as to maximize the news contribution to the forecast error variance decomposition (FEVD) of TFP across the average of multiple horizons, be orthogonal to the TFP surprise shock, and have zero impulse response of technology on impact.

To describe the procedure more formally, let

$$\mathbf{A}(\mathbf{L})\mathbf{z_t} = \mathbf{u_t}, \tag{2}$$

be a reduced-form vector autoregressive model, where $\mathbf{z_t}$ is the $K \times 1$ vector of variables in the model, with the exogenous variable, a_t, whose evolution is driven by own surprises and news shocks, ordered first, so that $\mathbf{z_t} = [a_t, \mathbf{f_t}]$, where $\mathbf{f_t}$ is a vector of forward-looking macroeconomic variables whose values may reflect expectations of future innovations in a_t. Next, assume that there exists a linear mapping from structural shocks $\epsilon_\mathbf{t}$ to reduced-form shocks $\mathbf{u_t}$ given by $\mathbf{u_t} = \mathbf{G}\epsilon_\mathbf{t}$. Then, the empirical model can be written as

$$\mathbf{z_t} = \mathbf{C}(\mathbf{L})\epsilon_\mathbf{t},$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{G}$ and $\mathbf{B}(\mathbf{L}) = \mathbf{A}(\mathbf{L})^{-\mathbf{1}}$. The impact matrix $\mathbf{G}$ must satisfy $\mathbf{GG'} = \mathbf{\Sigma}$, where $\mathbf{\Sigma}$ is the variance-covariance matrix of $\mathbf{u_t}$, but it is not unique. For some arbitrary orthogonalization $\mathbf{G}$, the Choleski decomposition providing a readily available alternative, the space of permissible impact matrices can be written as $\mathbf{GD}$, where $\mathbf{D}$ is an orthonormal matrix, so that $\mathbf{DD'} = \mathbf{I}$.

Defining the h-step-ahead forecast error for the vector of endogenous variables, $\mathbf{z_t}$, we have:

$$\mathbf{z}_{t+h} - E_{t-1}\mathbf{z}_{t+h} = \sum_{\tau=0}^{\infty} \mathbf{B}_\tau \mathbf{GD}\epsilon_{t+h-\tau}.$$

The forecast error variance of variable i to shock j at horizon h is

$$\phi_{i,j}(h) = \frac{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \mathbf{GD}\mathbf{e}_j\mathbf{e}_j'\mathbf{D'G'B}_\tau' \right) \mathbf{e}_i}{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \mathbf{\Sigma B}_\tau' \right) \mathbf{e}_i}, \tag{3}$$

where $\mathbf{e}_i$ is a selection vector with 1 in i^{th} place and zeros elsewhere.

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multiple news shocks.

Define $\alpha = \mathbf{D}\mathbf{e_2}$ as the second column of $\mathbf{D}$, so that the news shock is ordered second and the own surprise shock of a_t, given by its reduced-form residual from the VAR, is ordered first. The procedure assumes that the only two shocks, the own reduced-form shock (or surprise) and the news shock, account for all of the variability in the exogenous variable, a_t. The news shock is identified by solving for

$$\alpha^* = \arg\max \sum_{h=0}^{H} w_h \left(\frac{\sum_{\tau=0}^{h} \mathbf{B_{1,\tau}} \mathbf{G} \alpha \alpha' \mathbf{G}' \mathbf{B}'_{1,\tau}}{\sum_{\tau=0}^{h} \mathbf{B_{1,\tau}} \mathbf{\Sigma} \mathbf{B}'_{1,\tau}} \right), \tag{4}$$

so that $\mathbf{G}(1,j) = 0$, $\forall j > 1$, $\alpha_1 = 0$, $\alpha'\alpha = 1$, and $\sum_{h=1}^{H} w_h = 1$. The first condition suggests that only a_t's own reduced-form shock can have an impact on a_t at the zero horizon. The second constraint reinforces this idea by disallowing a_t's own surprise to enter the definition of the news shock. The third constraint ensures that the variance of the identified structural news shock is equal to 1. The general idea behind the procedure is that the weights given by the components of α are placed on $\mathbf{f_t}$'s reduced-form shocks so as to maximize the forecast error variance not explained by a_t's own surprise shock at forecast horizons greater than 0.

The identification procedure can be operationalized by recognizing that the denominator in (4) does not depend on α and exploiting the relationship between surprise and news shocks summarized in the constraints. Barsky and Sims (2011) then follow Uhlig (2003) and recast (4) as the following quadratic problem:

$$\hat{\alpha}^* = \arg\max \hat{\alpha}' \hat{\mathbf{V}} \hat{\alpha}$$

subject to

$$\hat{\alpha}'\hat{\alpha} = 1,$$

where, $\hat{\alpha}$ consists of all components of α other than the first one and $\hat{\mathbf{V}}$ is the lower $(K-1) \times (K-1)$ submatrix of

$$V = \sum_{h=0}^{H} \frac{w_h}{\bar{\sigma}^2_{1,h}} (H + 1 - h)(\mathbf{B_{1,h}} \mathbf{G})'(\mathbf{B_{1,h}} \mathbf{G}),$$

where $\bar{\sigma}^2_{1,h} = \sum_{\tau=0}^{h} \mathbf{B_{1,\tau}} \mathbf{\Sigma} \mathbf{B}'_{1,\tau}$ is independent of α. The optimality condition for this operationalized optimization problem implies that $\hat{\alpha}$ is the eigenvector associated with the maximum eigenvalue of $\hat{\mathbf{V}}$. Finally, the series for the news shock is given by $\alpha^{*\prime} \mathbf{G}^{-1} \mathbf{u_t}$ and impulse responses
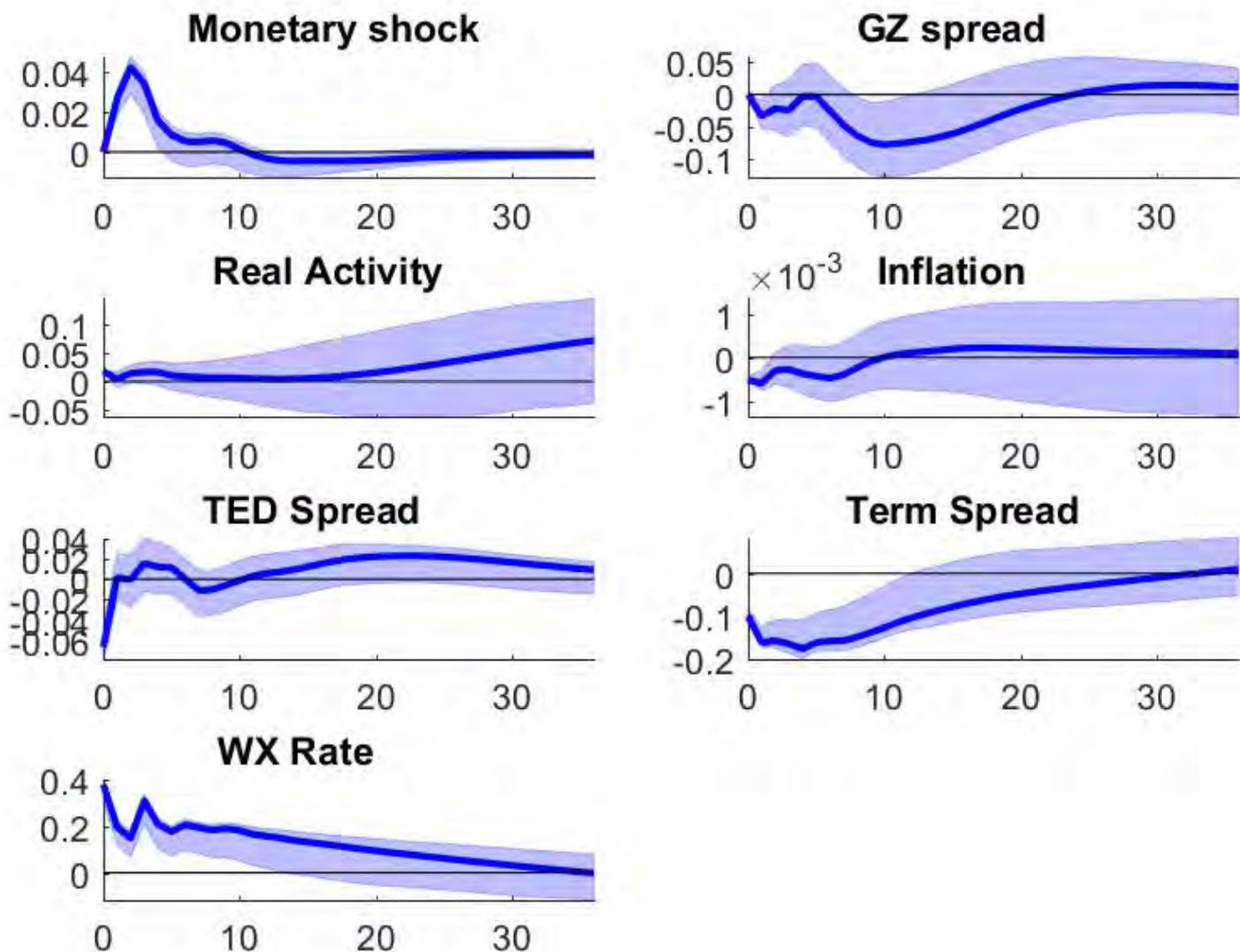
Figure 4: Impulse responses of macroeconomic variables to monetary news. 90% confidence intervals from Killian's (1998) bootstrap with 1,000 replications are the shaded areas.

and historical decompositions of endogenous variables due to the shock are given by $\mathbf{B}(\mathbf{L})\mathbf{G}\alpha^*\mathbf{u}_t$.

In a closely related paper, Ben Zeev et al (2016) construct a measure of monetary policy news using quarterly *ex post* data with an *ad hoc* Taylor rule specification estimated over the sample through 2007Q4, before the Great Recession. In an attempt to better disentangle monetary news from credit market disruptions, they place Taylor Rule residuals first and the Gilchrist and Zakrajsek (2012) credit spread (GZCS) second while the rest of $\mathbf{z_t}$ comprises a vector of forward-

looking macroeconomic variables. This requires several modifications to the Barsky-Sims procedure. First, the selection vector $\mathbf{e_i}$ in (3) now has zeros in the first two entries to ensure that monetary news does not have contemporaneous effects either on the monetary shock or GZCS, implying that $\mathbf{G}(1,j) = \mathbf{G}(2,j) = 0, \ \forall j > 1$. Second, the vector of weights of the reduced-form residuals for the macroeconomic variables is now the third column in $\mathbf{D}$, with the first *two* entries set to zero ($\alpha_1 = \alpha_2 = 0$). The matrix of variables in the VAR system $\mathbf{z_t}$ is given by the three-month average monetary policy surprise identified in Section 3,[7] ϵ_t, the GZCS, g_t, and $\mathbf{f_t}$, given by the unemployment rate, log CPI, TED spread, term spread, and the Wu-Xia (2016) series for the shadow short-term nominal interest rate.

Figure 4 displays the impulse response functions (IRFs) of the variables in $\mathbf{z_t}$ to the monetary news shock. Note that since α^* is identified only up to the sign, the vector is multiplied by -1 if the cumulative response of the monetary shock after 5 months is negative. The response of monetary shock peaks at about 3 months. Higher expected FFR depresses the GZCS, although the effect peaks only after about 10 months. The news shock has negligible effect on real activity but successfully depresses prices on impact. It reduces the TED spread, flattens the yield curve, and increases the short-term nominal interest rate—effects that are all consistent with an anticipated monetary tightening.

Figure 5 provides the time series for the identified monetary news shock. Interestingly, while there were large negative news shocks immediately prior and during the Great Recession, they are not as large in absolute terms as the news shocks during the recession of 1991 or around 2000, suggesting that the Fed could have potentially adopted a more aggressive policy stance with respect to forward-looking policy. However, the negative balance of news shocks during the Great Recession suggests that the Federal Reserve primarily employed "forward guidance" on the evolution of the equivalents of changes in the short-term interest rate in the direction of future *reductions* in the rate target. This directional aspect will be important in the discussion of the responses of measures of systemic risk to monetary news and surprises.

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[7]The averaging is applied because the Greenbook data corresponds to the eight FOMC meetings per year, resulting in regularly spaced misses in the monthly data.
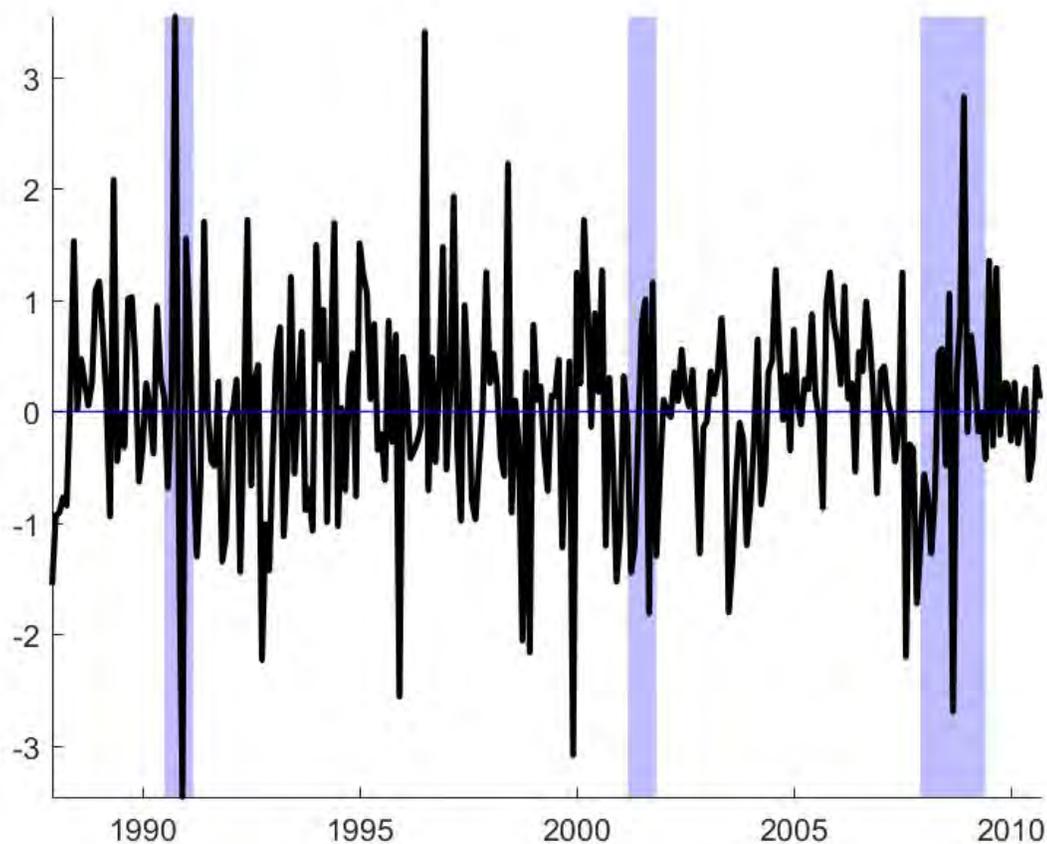
Figure 5: Monetary news shock. (Shaded areas are the recessions defined by the National Bureau for Economic Analysis (NBER).

5 Monetary Surprises and News: Effect on Systemic Risk Measures

This section studies the effect of the monetary policy news shocks given in Figure 5 on the systemic risk measures, r_t, discussed in Section 2. The framework for evaluating their dynamic impact is given by the single-equation application of Jorda's (2005) multivariate local projections framework for estimating impulse response functions. Garin et al (2016) and Wieland (2016) have applied this methodology to study the transmission of supply shocks to macroeconomic variables at the ZLB, whereas Auerbach and Gorodnichenko (2013) and Ramey and Zubairy (2014) have applied it to study the transmission of fiscal policy. To disentangle the effects of monetary news and surprises

at the ZLB from normal conditions, I estimate the following series of equations:

$$r_{t+h} = \alpha^h + \beta^h p_t + \sum_{q=1}^{Q} \gamma_q^h r_{t-q} + \sum_{q=1}^{Q} \phi_q^h p_{t-q} + Z_t \left[\alpha_z^h + \beta_z^h p_t + \sum_{q=1}^{Q} \gamma_{zq}^h r_{t-q} + \sum_{q=1}^{Q} \phi_{zq}^h p_{t-q} \right], \quad (5)$$

where p_t is the policy shock (either monetary news or surprise), Z_t is a dummy variable that is set to 1 at the zero lower bound (starting in October 2008 until the end of the sample in December 2010) and is zero otherwise, β^h maps out the impulse responses of systemic risk measures as h increases over the full sample whereas $\beta^h + \beta_z^h$ does the same under the zero lower bound.[8] As is standard in the local projections literature, 90% confidence intervals are obtained with Newey-West HAC standards errors.

5.1 Institution-specific Contributions to Systemic Risk

Figure 6 describes the impulse responses to monetary news and surprises for the four variables that sum institution-specific risk factors up to the aggregate level. All four measures have statistically insignificant responses to monetary surprises, with confidence intervals widening appreciably at the ZLB. Reponses to monetary news shocks, on the other hand, generate more appreciable effects. Three out of the four measures—CoVaR, ΔCoVaR, and MES—have negative impulse responses to anticipated interest rate increases during the full sample, suggesting that future interest rate hikes reduce these measures of systemic risk. However, their amplitude is quite small and the upper confidence interval branches are barely below the zero horizontal line of no response. In contrast, the amplitude of the all four variables'—including MES-BE—responses to monetary news shocks during the ZLB episode is about 5 to 10 times larger in absolute value than over the full sample, is statistically significant and *positive*, suggesting that it was announcements of future interest rate *decreases* that reduced these measures of systemic risk.

5.2 Measures of Comovement and Contagion

Figure 7 describes the impact of monetary news and surprises on measures of comovement and contagion. Impulses responses of all four variables to monetary news shocks invariably include

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[8]Due to the few observations during the ZLB and even shorter samples for some measures of systemic risk, I set $Q = 1$.
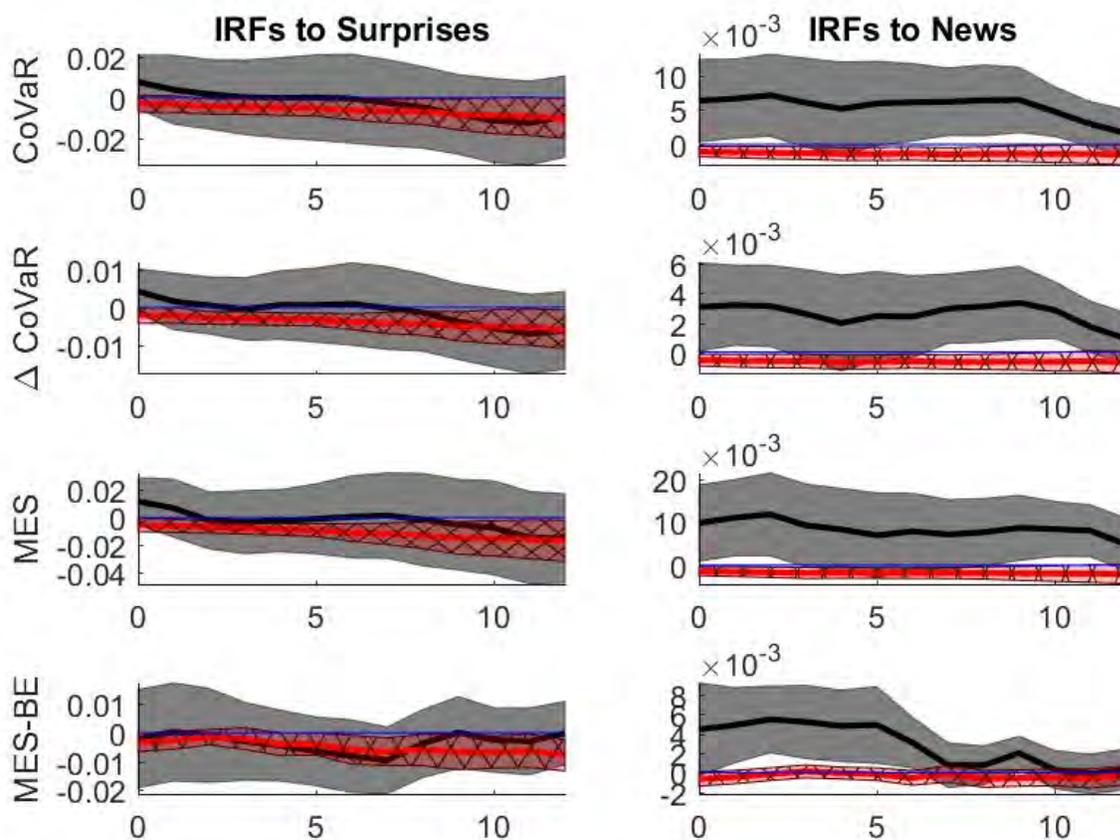
Figure 6: Impulse responses of institution-specific systemic risk measures to monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (crosshatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

the no-response horizontal line at zero, both over the full sample and at the ZLB. Two measures have statistically significant responses to news over the full sample: the absorption ratio decreases in response to future rate increases and its change increases. However, both of these response amplitudes appear to be small. Monetary policy shocks—both news and surprises—appear to have at best a negligible effect on measures of comovement and contagion.

5.3 Measures of Volatility and Instability

Figures 8 and 9 display the IRFs of measures volatility and instability. All six measures have statistically insignificant impulse responses to monetary surprises at the ZLB; real volatility, turbulence,
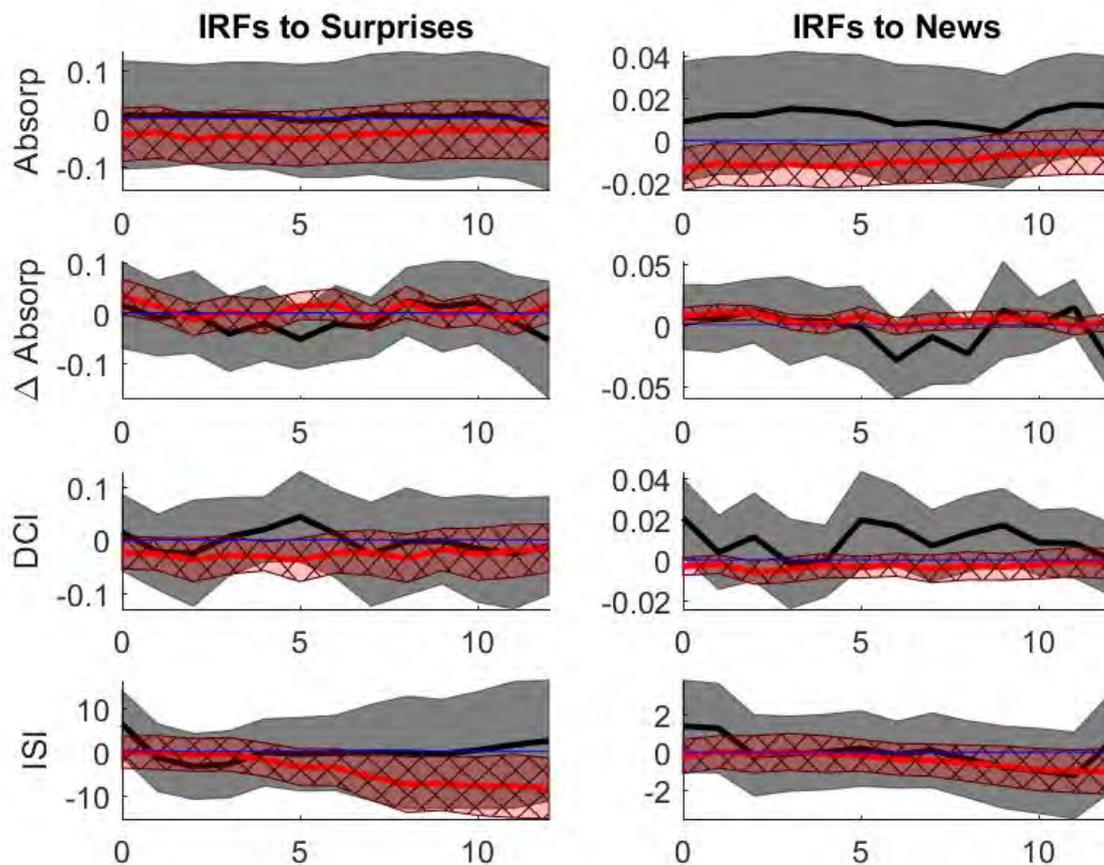
Figure 7: Impulse responses of measures of comovement and contagion to monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

and CatFin have marginally significant but quantitatively unimportant responses to surprises over the full sample. Impulse response to news shocks are also mostly insignificant and small (but consistently negative at the mean) over the full sample. However, for four measures—real volatility, turbulence, CatFin, and market leverage, they are positive, large, and statistically significant. The mean response of book leverage is also large and positive but statistically insignificant, whereas size concentration has essentially zero response with wide confidence intervals. Therefore, it appears that expectations of equivalents of discretionary interest rate decreases at the ZLB have large and statistically significant effects in terms of reducing most measures of volatility and instability.
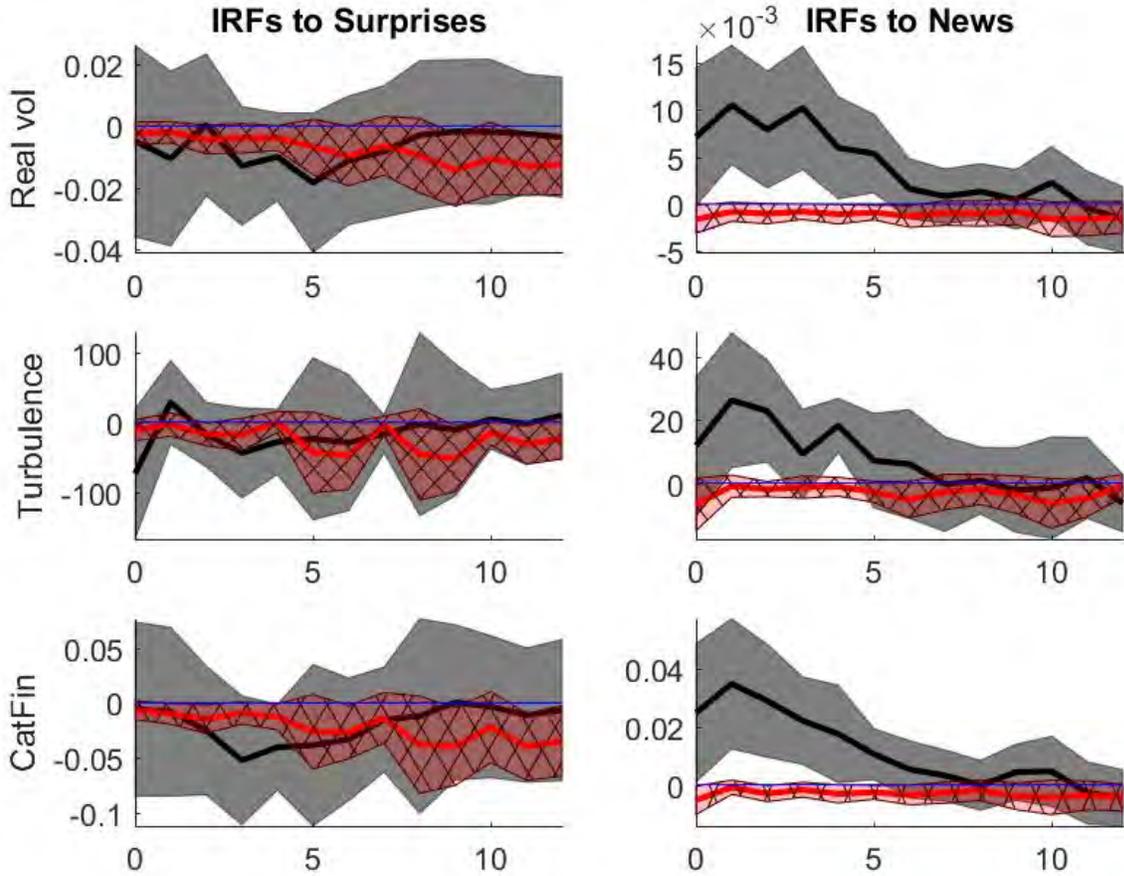
Figure 8: Impulse responses of measures of volatility and instability to monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

5.4   Measures of Liquidity and Credit

Finally, Figures 10 and 11 show the impulse responses of measures of liquidity and credit, as well as the "index-of-indexes" PQR measure discussed in 2. None of the measures significantly respond to monetary surprises at the ZLB and over the full sample only the term and default spreads have sizable, negative, and statistically significant impulse responses in line with the standard economic intuition. Responses to monetary news shocks over the full sample appear to be mostly negative, small in magnitude, and largely insignificant except for term spread over the full 12-month horizon, TED spread close to impact. At the ZLB, on the other hand, IRFs to news are large and significant for the four variables other than AIM and term spread. TED, default, and GZ spread responses
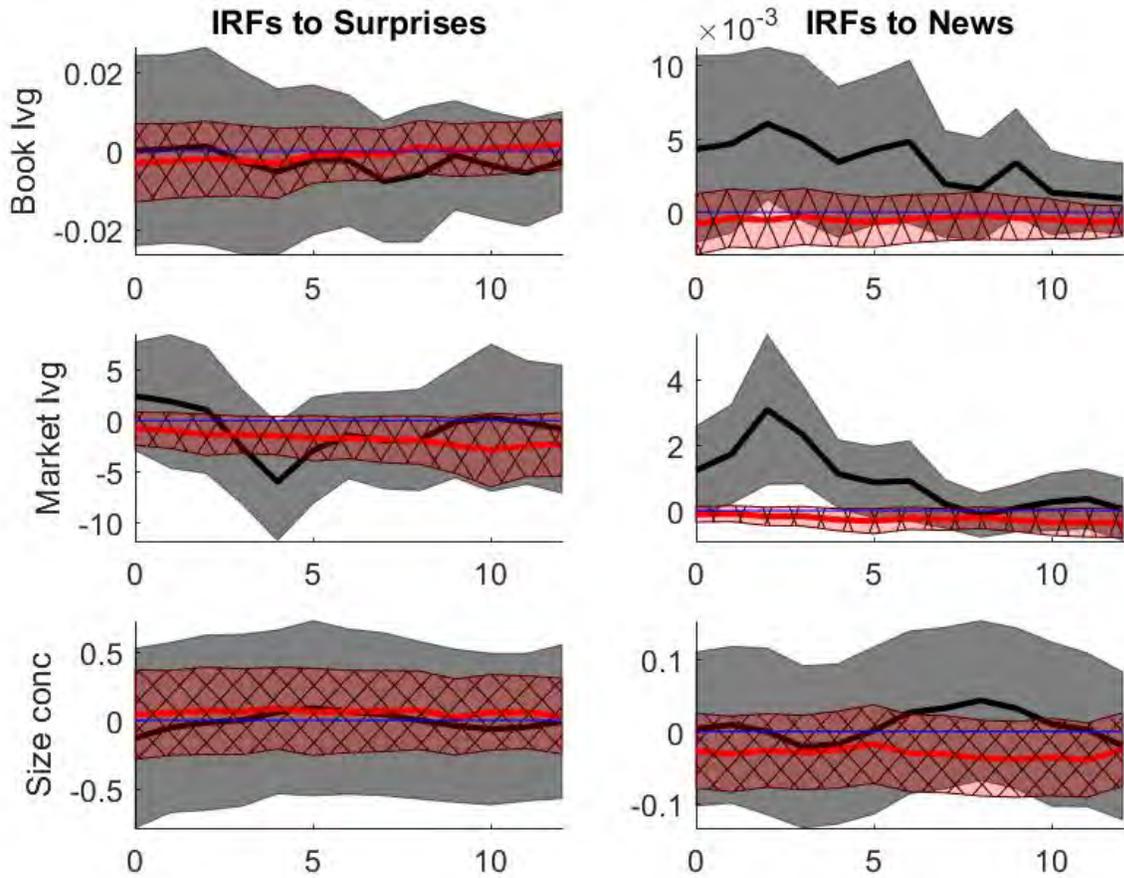
17

Figure 9: Impulse responses of measures of volatility and instability (continued from previous figure) to monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

are all positive and the PQR response is negative, which is consistent with the anticipated interest rate *decreases* reducing these four measures of systemic risk.

In sum, these findings suggest that monetary policy surprises have virtually no effect on measures of systemic risk other than the term spread over the full sample or at the ZLB. Measures of comovement and contagion do not appear to respond to either monetary news or surprises. For most other measures, monetary news shocks tend to generate small reductions in systemic risk due to anticipated *contractionary* future monetary policy over the full sample and large reductions due to anticipated *expansionary* policy at the ZLB.
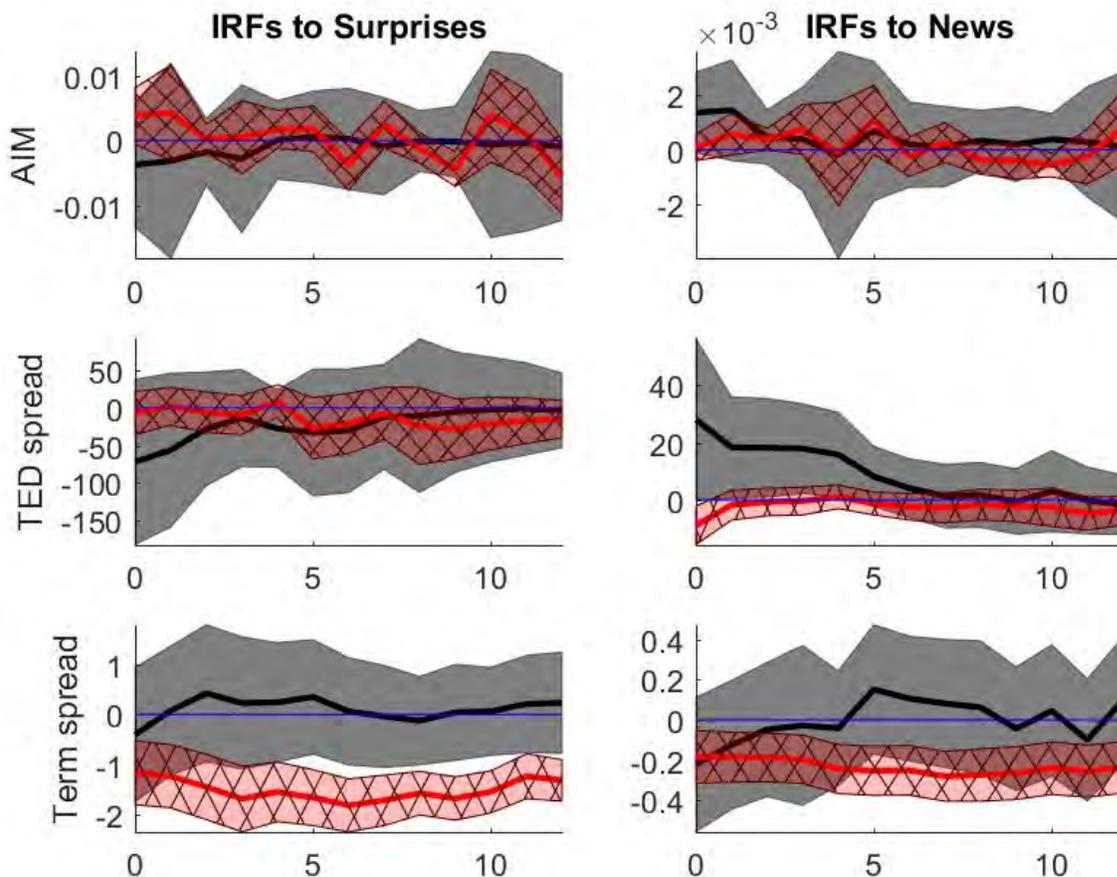
Figure 10: Impulse responses of measures of volatility and instability to monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

6 Conclusion

This paper combined a measure of the shadow target FFR during the period of the zero lower bound with the Greenbook forecasts to construct a measure of monetary policy surprises. Using a recent advance in the identification of news shocks that affect an exogenous variable of interest with a lag, this paper also identifies monetary policy news, including during the Great Recession. Impulse responses obtained using local projections suggest that monetary surprises have minimal impact on measures of systemic risk before and during the ZLB. Monetary news, on the other hand, have a minor impact on systemic risk over the full sample, suggesting that higher expected interest rates reduce systemic risk. Perhaps more importantly, at the ZLB, it is the *lower* interest rate news
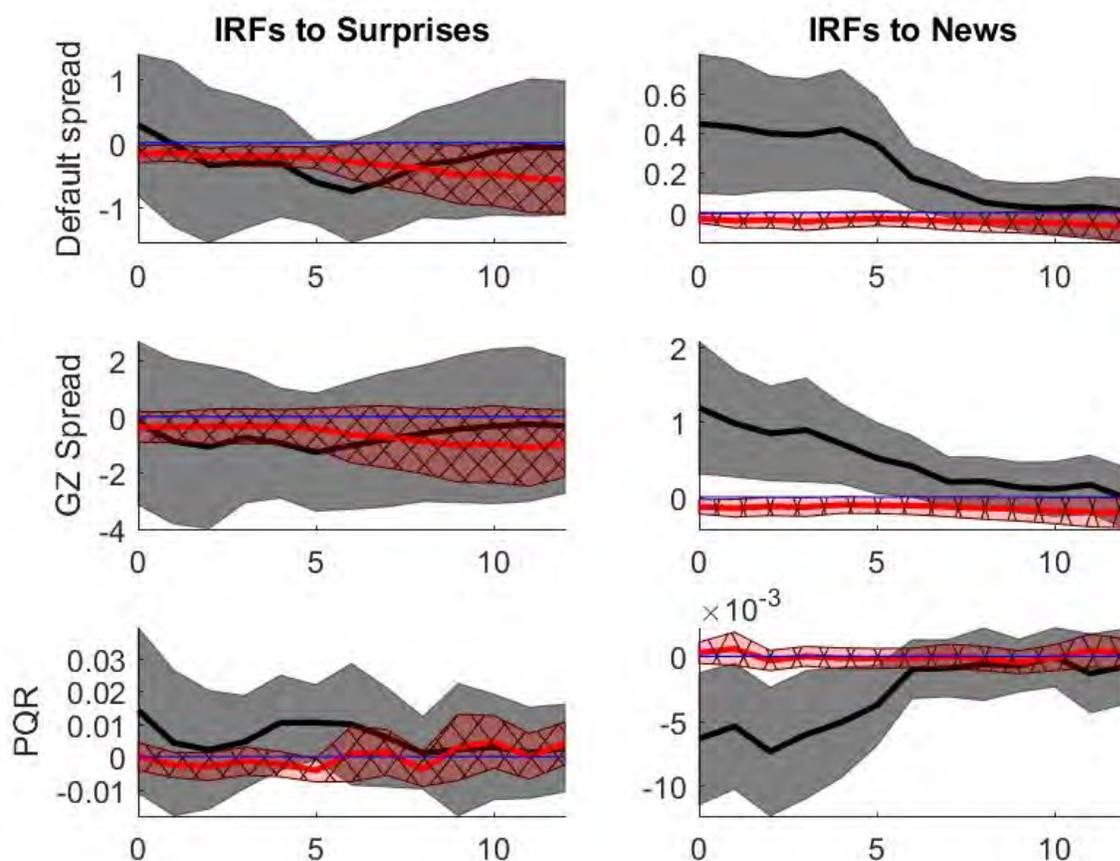
Figure 11: Impulse responses of measures of liquidity and credit (continued from previous figure) to monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

that are associated with large declines in the measures of systemic risk. Therefore, it appears that the Federal Reserve's commitment to low interest rates during the crisis was successful in reducing systemic risk.

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