

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 of the Great Recession of 2008-2009 and the 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 and impulse responses from the method of local projections, it shows that *contractionary* monetary surprise and news shocks tended to reduce systemic risk measures over the full sample. In contrast, *expansionary* monetary news shocks reduced systemic risk at the zero lower bound, whereas surprises had little effect. These findings suggest that the Federal Reserve's efforts at providing expansionary forward guidance at the zero lower bound were successful in stabilizing measures of systemic risk during the Great Recession.

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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 concern with 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 short-term nominal 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) provided 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 popularity among academics and practitioners 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 a means of evaluating its effectiveness.

The Great Recession of 2008-2009 challenged the standard analysis of monetary policy 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 lower the current interest rate below zero, sends signals to the

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

²Krugman (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.

economic agents about its future conduct of 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 as-of-now 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 in the spirit of the framework developed by Romer and Romer (2004). Bluedorn et al (2017) and subsequently Wieland and Yang (2017) have recently updated these series through 2007, stopping before the Great Recession. Since during the crisis the FFR reached the ZLB, 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 is similar to that of Ben Zeev et al (2016) with several important distinctions: monetary shocks are defined using the Romer and Romer (2004) approach that relies on the real-time information available to the Fed; monetary news shocks are derived in the VAR model estimated at the monthly as opposed to quarterly 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 *contractionary* monetary surprises and news tended to reduce the alternative measures of systemic risk before the ZLB, their economic impact was relatively small. In contrast, at the ZLB, monetary surprises had virtually no effect on systemic risk, whereas *expansionary* news resulted in large reductions of alternative systemic risk measures. These results

³For 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).

suggest that forward guidance, as captured by monetary news shocks, can be a powerful tool in mitigating systemic risk under severely adverse conditions.

The rest of the paper is organized as follows. Section 2 describes the data used in this paper’s empirical exercises. Section 3 details the construction of monetary policy surprise shocks before 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. 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 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 to model the information available to the Federal Reserve in real time as it sets the federal funds rate target. To allow for the continuity into the ZLB period, I use the Greenbook Financial Assumptions projections for the current federal funds rate (FFR) target, which 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.⁴ 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. Discrepancies between the two series in the early part of the sample are motivated by the departures of the actual FFR from the Fed’s target level. However, these dis-

⁴Monetary policy shocks obtained using the timing assumptions imposed on the target FFR in this paper are virtually identical, in definition and effect on macroeconomic variables, to the ones obtained by Romer and Romer (2004) and Wieland and Yang (2017) using the narrative approach applied to the FOMC meeting transcripts and minutes.

crepancies do not affect the set of the exercises below, since it is only the post-2008 portion of the Wu-Xia rate that is used, i.e. 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. Finally, in the specification that uses federal funds futures to identify the monetary news shock, I use the closing prices as of the date prior to the FOMC meeting of the second expiring contract on 30-day futures obtained from Haver Analytics. Since those series are only available starting in October 1988, that specification leaves out a small number of observations at the beginning of the sample.

Estimates of monetary news—as opposed to the standard surprise—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 their Wu-Xia (2016) rate counterparts, reduced-form innovations in these series will be used to identify monetary news shocks.

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 recently 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 (2017) and its modification, MES-BE, due to Brownlees and Engle (2017);
- *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) 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;⁵

⁵The ISI series end in April 2010.

- *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 is 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;⁶
- *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 predicting the 10th percentile of industrial production growth. 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. To simplify exposition, PQR is added to the liquidity and credit group, even though it encompasses all of the above measures of systemic risk.

The next two sections outline the construction of the monetary policy drivers of these systemic risk measures. Section 3 blends the Romer and Romer (2004) approach to constructing monetary surprises with the Wu-Xia (2016) shadow rate to extend the former into the ZLB setting. Section 4 adopts the Barsky and Sims (2011) approach to construct a measure of monetary news shock given these exogenous monetary surprises. Finally, Section 6 offers concluding remarks.

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 that includes lags of the nominal interest rate and other macroeconomic variables, as would be the case in the vector autoregressive (VAR) framework, estimated on the final vintage of the

⁶The Gilchrist and Zakrajsek (2012) credit spread series end in September 2010.

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 can then be given by:

$$\Delta f f_m = \alpha + \beta f f_{m-1} + \sum_{i=-1}^H \gamma_i y_{m,i} + \sum_{i=-1}^H \lambda_i (y_{m,i} - y_{m-1,i}) + \sum_{i=-1}^H \varphi_i \pi_{m,i} + \sum_{i=-1}^H \theta_i (\pi_{m,i} - \pi_{m-1,i}) + \rho' \mathbf{X}_m + \epsilon_m, \quad (1)$$

where $\Delta f f_m$ 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.⁷ 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 2010 materially

⁷Wieland and Yang (2017) have also updated the Romer and Romer (2004) shocks through 2007 at alternative frequencies. The timing on the federal funds targets follows Bluedorn et al. (2017). See 4 for additional information.

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 2008. 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.

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

The exercise of identifying monetary news shocks carried out below follows the 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.⁸ News shock series is defined as the weighted average of reduced-form residuals *for all endogenous 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

$$\mathbf{A}(\mathbf{L})\mathbf{z}_t = \mathbf{u}_t, \quad (2)$$

⁸Alternatively, 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 multiple news shocks.

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 ϵ_t to reduced-form shocks $\mathbf{u}_t$ given by $\mathbf{u}_t = \mathbf{G}\epsilon_t$. Then, the empirical model can be written as

$$\mathbf{z}_t = \mathbf{C}(\mathbf{L})\epsilon_t,$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{G}$ and $\mathbf{B}(\mathbf{L}) = \mathbf{A}(\mathbf{L})^{-1}$. The impact matrix $\mathbf{G}$ must satisfy $\mathbf{G}\mathbf{G}' = \mathbf{\Sigma}$, 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 $\mathbf{G}\mathbf{D}$, where $\mathbf{D}$ is an orthonormal matrix, so that $\mathbf{D}\mathbf{D}' = \mathbf{I}$.

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

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

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

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

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

Furthermore, one can 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

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

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

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

where $\bar{\sigma}_{1,h}^2 = \sum_{\tau=0}^h \mathbf{B}_{1,\tau} \boldsymbol{\Sigma} \mathbf{B}_{1,\tau}'$ 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 $\alpha^{*'} \mathbf{G}^{-1} \mathbf{u}_t$ and impulse responses and historical decompositions of endogenous variables due to the shock are given by $\mathbf{B}(\mathbf{L}) \mathbf{G} \alpha^* \mathbf{u}_t$. Importantly, 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.

4.1 Results from the Baseline Specification

The baseline specification uses the RR2004-style monetary policy surprise shocks as a measure of a_t , whereas $\mathbf{f}_t$ is 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. The response of monetary

shock peaks at about 3 months. 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. Unemployment significantly increases on impact but quickly turns insignificant, whereas the price level drops on impact and becomes insignificant at longer horizons. Monetary news shocks, therefore, generate macroeconomic effects that are consistent with standard theory.

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.

4.2 Robustness Checks for Futures and Credit Market Frictions

Ben Zeev et al (2016) argue in a related paper that the use of federal funds futures (FFF) may help identify monetary news shocks and, furthermore, that this identification hinges on being able to disentangle monetary news from credit market disruptions. More specifically, they 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.⁹ They use FFF in their set of variables in the VAR as a measure that could capture future movements in the federal funds rate. Similarly, in one robustness exercise, I augment $\mathbf{f}_t$ by FFF taken as the second expiring contract on 30-day futures as of the day prior to the FOMC meeting.

Furthermore, to purge credit market disruptions from monetary news, Ben Zeev et al (2016) 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 approach requires several modifications to the Barsky-Sims procedure. First, the selection vector $\mathbf{e}_i$ in (3)

⁹For a recent discussion of the role of credit spreads in the identification of monetary policy shocks using SVAR models, see Caldara and Herbst (2016).

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 $\mathbf{f}_t$ remains unchanged. However, a better gauge of purely credit market disruptions may be the excess bond premium (EBP), also introduced by Gilchrist and Zakrajsek (2012), that nets out from the GZCS the default risk premium that may be driven by broader macroeconomic conditions.¹⁰ Therefore, both the GZCS and the EBP are used to augment $\mathbf{z}_t$ ordered second after a_t to gauge the robustness of the monetary news shock identification procedure with respect to alternative measures of credit market disruptions.

Figure 6 reports the results for the three additional specifications, with mean impulse responses in solid blue and the mean impulse responses from the baseline specification designated by the dashed black line. The differences in impulse responses of the variables included in the baseline $\mathbf{f}_t$ appear to be fairly minor and do not change the main intuition that follows from the baseline results.

Finally, Table 1 presents the estimated α^* from all four specifications. Unemployment and log CPI have relatively low weights across all three specifications, suggesting that the interest rate measures are the main determinants of the monetary policy news shocks.¹¹ Since the presence of federal funds futures and credit spreads does not appear to materially affect the definition of the news shocks or the impulse responses to it, below I only use the series obtained from the baseline specification.

5 Monetary Surprises and News: Effect on Systemic Risk Measures

This section studies the effect of 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

¹⁰Favara et al (2016) provide a description of the updated GZCS and EBP series.

¹¹Similar results obtain with other measures of real activity and price level.

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.¹² 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 7 describes the impulse responses to monetary news and surprises for the four variables that sum institution-specific risk factors up to the aggregate level. Both surprises and news are rescaled by their standard deviations whose values are listed at the top of each column. All four measures exhibit responses to monetary surprises that are statistically significant at the 90% level with contractionary shocks implying small reductions in systemic risk. However, the confidence intervals widen appreciably at the ZLB and none of the responses to monetary surprises, except $\Delta CoVaR$ on impact, are significant at any horizon. Responses to monetary news shocks over the full sample are similar to surprises in that their contractions result in small but statistically significant decreases at the 90% level. At the ZLB, however, impulse responses to news change sign, suggesting that expansionary, rather than contractionary, monetary news yield decreases in systemic risk, are statistically significant over longer horizons, and are larger in size on impact by factors ranging from about 5 to 15, depending on the specific measure. These results suggest that

¹²Due to the few observations during the ZLB and even shorter samples for some measures of systemic risk, I set $Q = 1$.

it was announcements of future interest rate *decreases* that reduced these measures of systemic risk rather than the unexpected monetary policy actions.

5.2 Measures of Comovement and Contagion

Figure 8 describes the impact of monetary news and surprises on measures of comovement and contagion. Impulses response confidence intervals of all four variables to monetary surprise shocks invariably include the no-response horizontal line at zero, both over the full sample and at the ZLB, with the exception of DCI and ISI that have significant responses at about 5 and 10-12 months out, respectively. Similarly, impulse responses to monetary news do not show a consistent pattern and are generally small and insignificant. Exceptions are: contractionary news reduce absorption and increase its change over the full sample but in both cases the effects are relatively small; expansionary news reduce the DCI, with large, statistically significant responses on impact and 5 months out. On balance, therefore, 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

Figure 9 displays the IRFs of measures volatility and instability. All six measures have statistically insignificant impulse responses to monetary surprises at the ZLB; real volatility, turbulence, 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 five measures—real volatility, turbulence, CatFin, book leverage, and market leverage—they are positive, large, and statistically significant. Only 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 had large and statistically significant effects in terms of reducing most measures of volatility and instability during the Great Recession.

5.4 Measures of Liquidity and Credit

Finally, Figure 10 shows 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, while over the full sample only the term and default spreads have 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 (except for PQR because of its definition) and small in magnitude; they are significant at the 90% significance level for TED, term, default, and GZ spreads. At the ZLB, on the other hand, IRFs to news are large and consistent with expansionary news reducing systemic risk but statistically significant for only default and GZ spreads, as well as PQR.

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.

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 recent advances 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 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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A Tables

Table 1: Estimated α^* by Specification

Variable	Baseline	FF Futures	GZ Spread	EBP Spread
Mon shock	0.000	0.000	-0.000	-0.000
Credit/FFF	—	0.052	0	0
Unemp Rate	0.094	0.110	0.069	0.069
log(CPI)	-0.136	-0.189	-0.061	-0.061
TED Spr	-0.550	-0.572	-0.468	-0.468
Term Spr	-0.217	-0.234	-0.372	-0.372
WX Rate	0.789	0.753	0.797	0.797

B Graphs

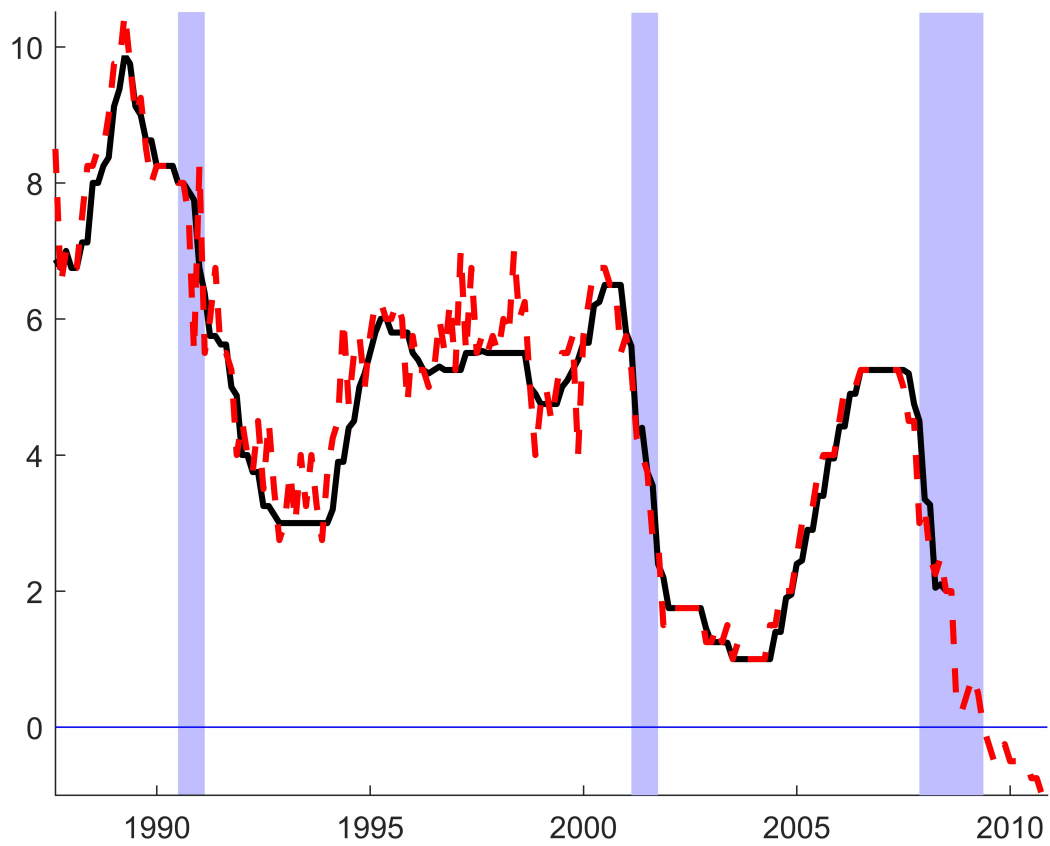


Figure 1: Greenbook zero-horizon federal funds rate target (solid black line) and the Wu-Xia shadow interest rate (dashed red line) rounded to the nearest 25 basis points.

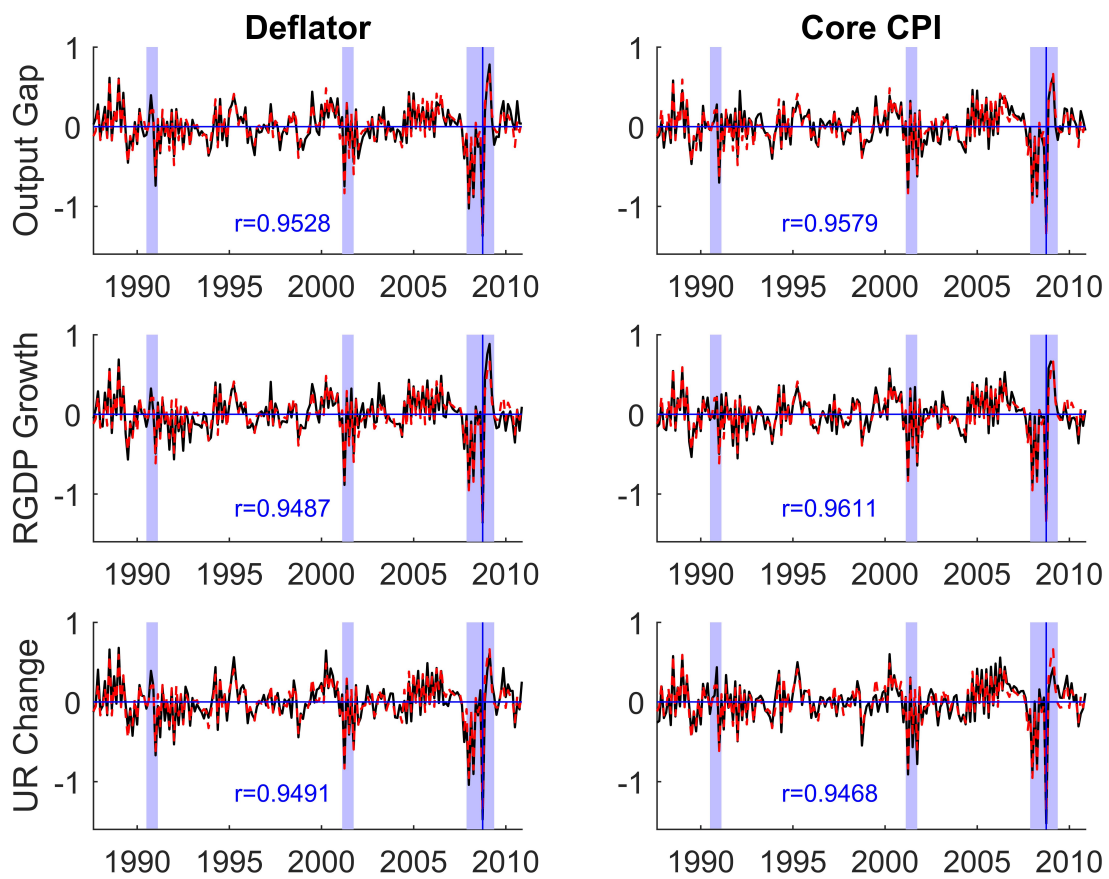


Figure 2: Monetary policy surprises from individual combinations of measures of inflation and real activity (dashed red line) vs. average across all six specifications (black solid line).

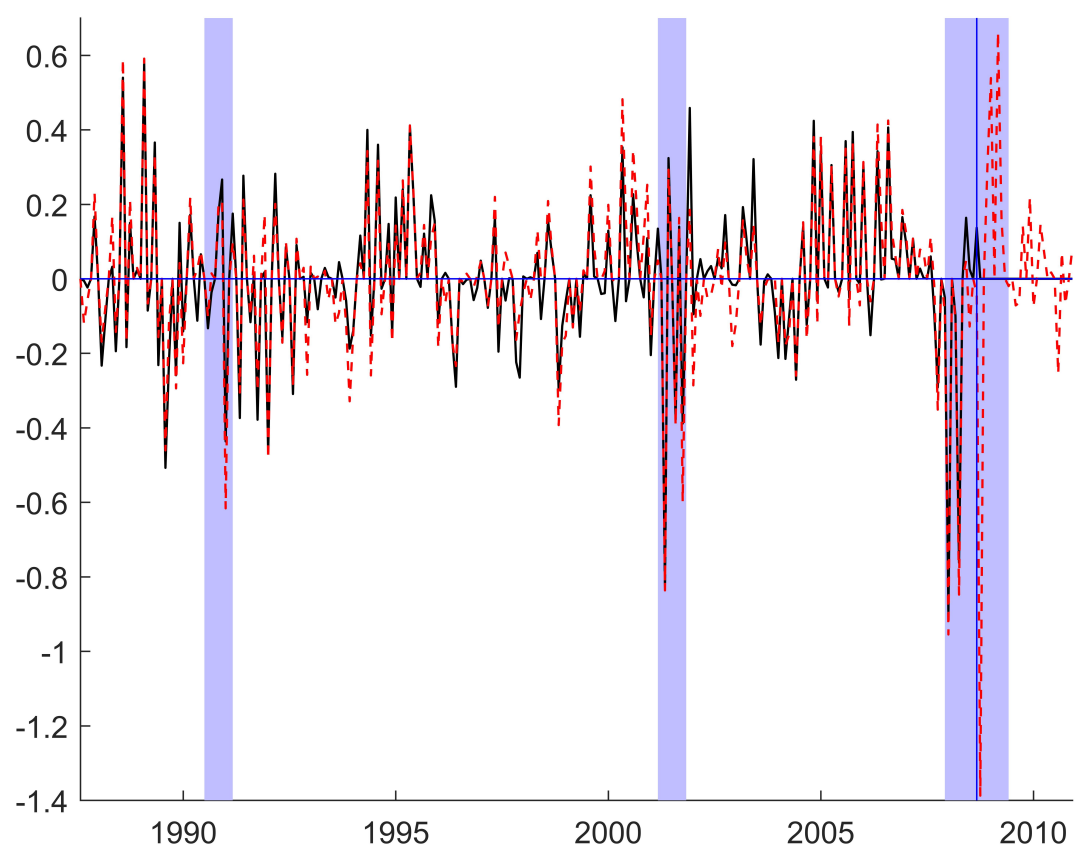


Figure 3: Monetary policy surprises using Wu-Xia (2016) series for 2008-2010 (dashed red line) vs. the surprises estimated on actual Greenbook FFR through September 2008 (black solid line). (Shaded areas are the recessions defined by the National Bureau for Economic Analysis (NBER)).

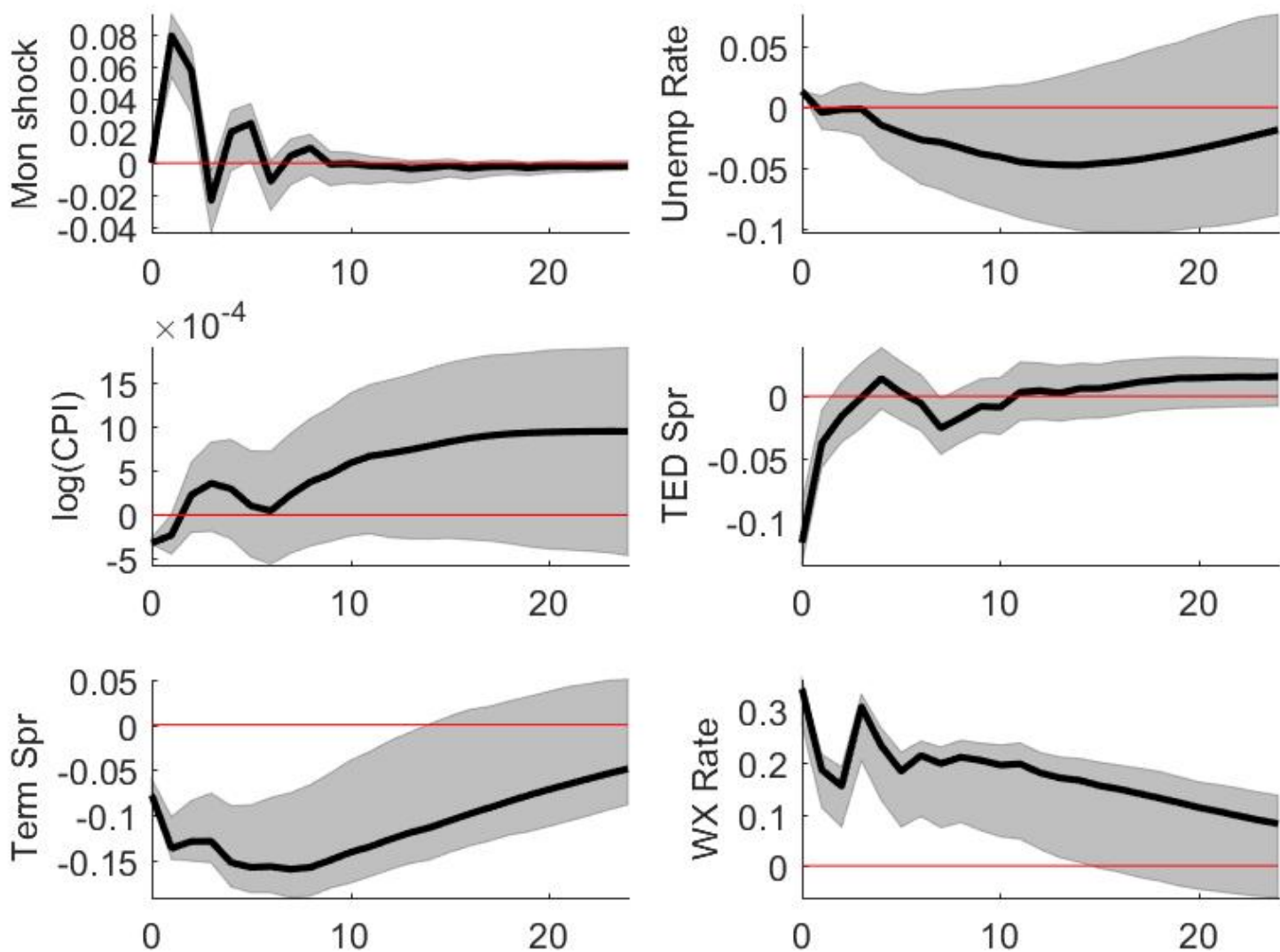


Figure 4: Impulse responses of macroeconomic variables to monetary news; baseline specification. 90% confidence intervals from Killian's (1998) bootstrap with 1,000 replications are the shaded areas.

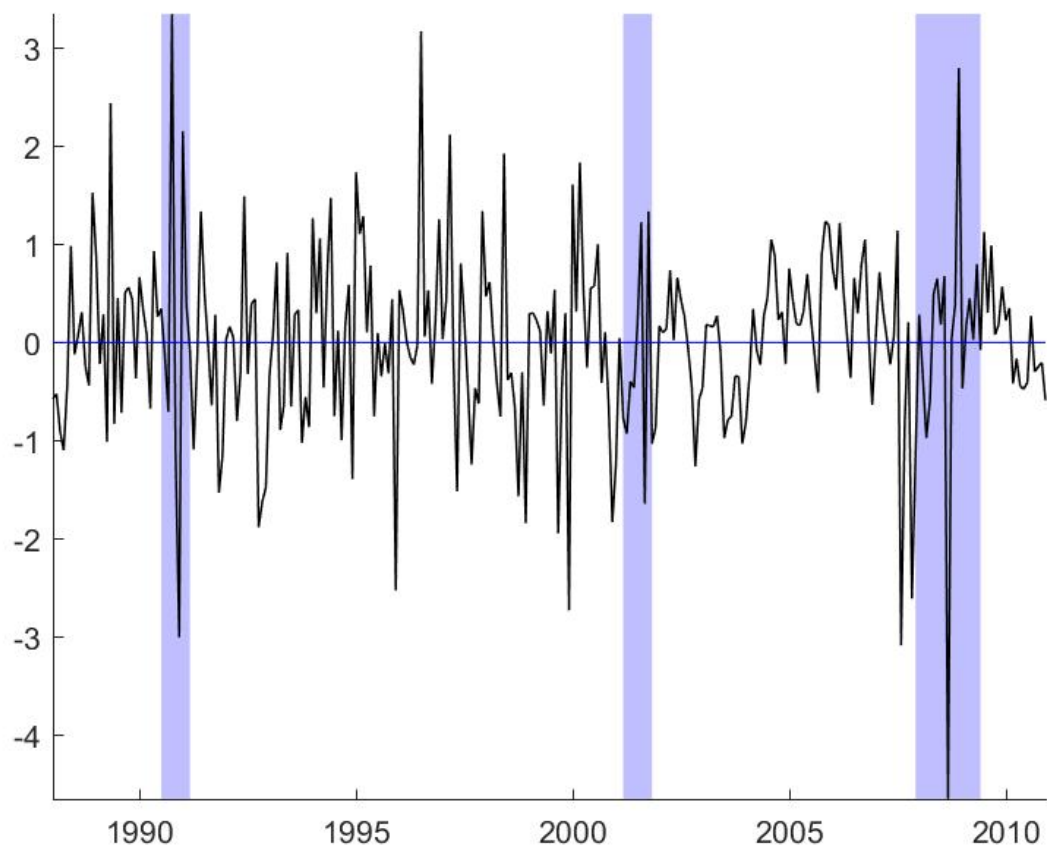


Figure 5: Monetary news shock. (Shaded areas are the recessions defined by the National Bureau for Economic Analysis (NBER)).

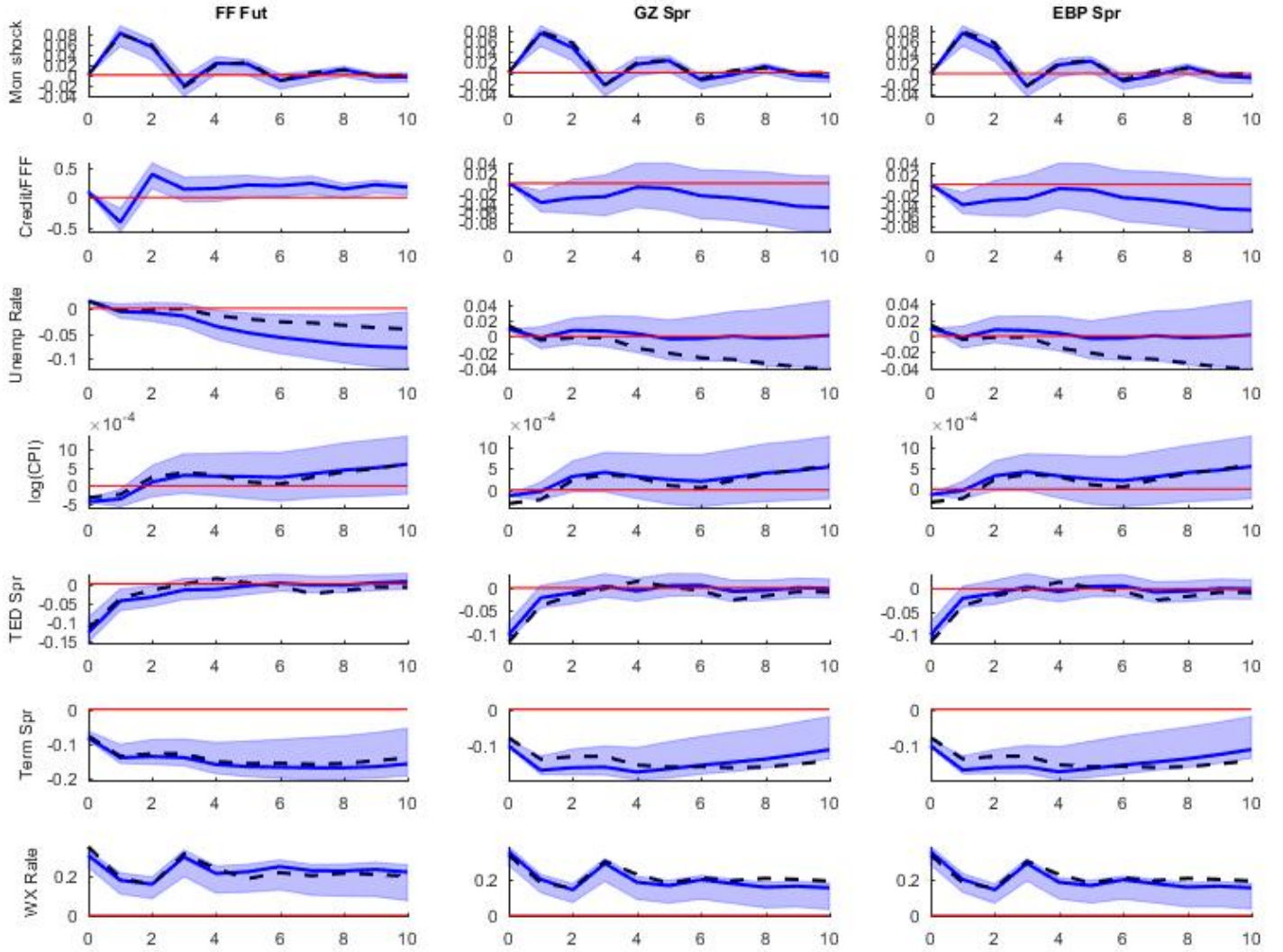


Figure 6: Impulse responses of macroeconomic variables to monetary news; robustness checks. Mean impulse responses in blue; 90% confidence intervals from Killian's (1998) bootstrap with 1,000 replications are the shaded areas; dashed black lines designated mean impulse responses from the baseline specification.

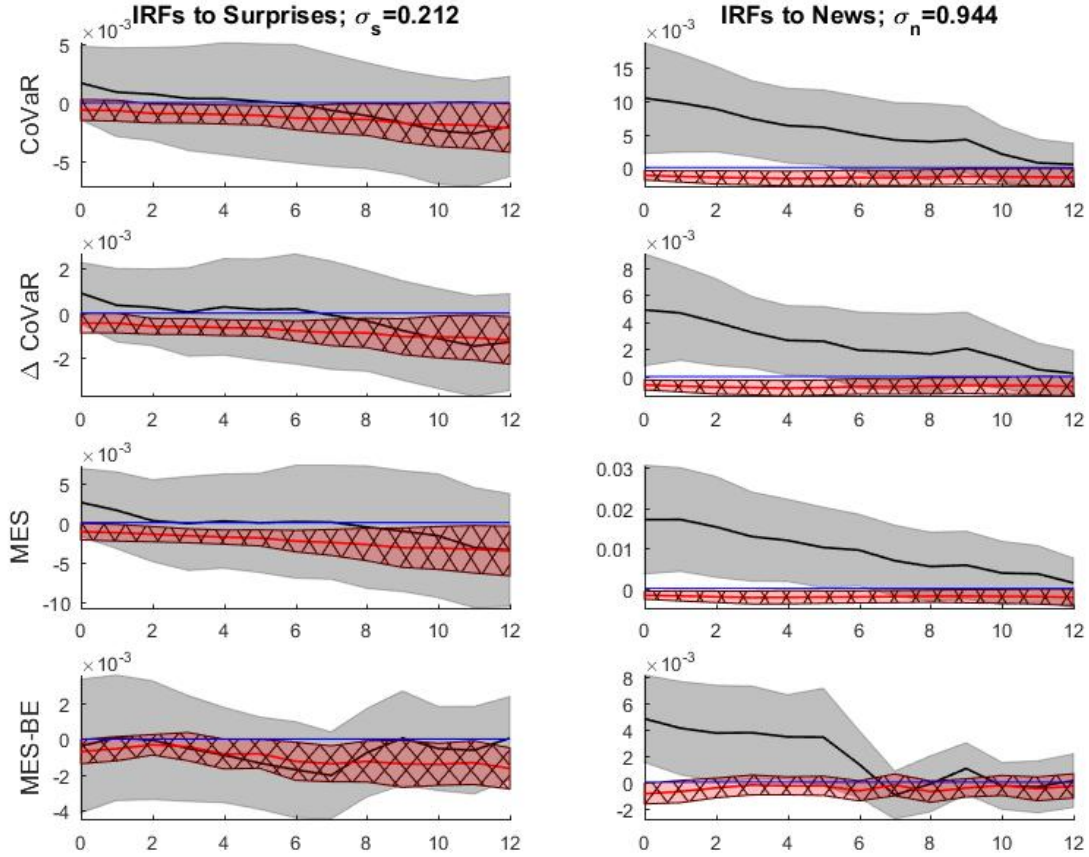


Figure 7: Impulse responses of institution-specific systemic risk measures to one standard deviation of monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

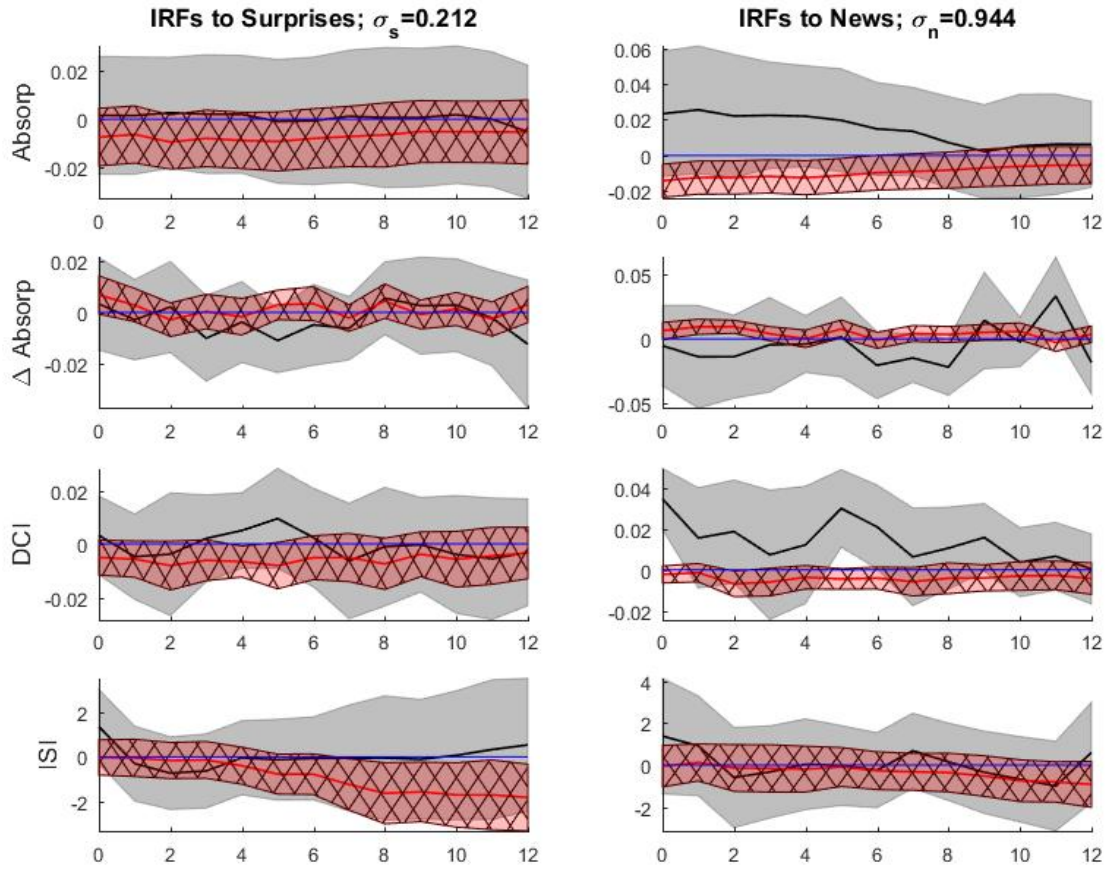


Figure 8: Impulse responses of measures of comovement and contagion to one standard deviation of monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.

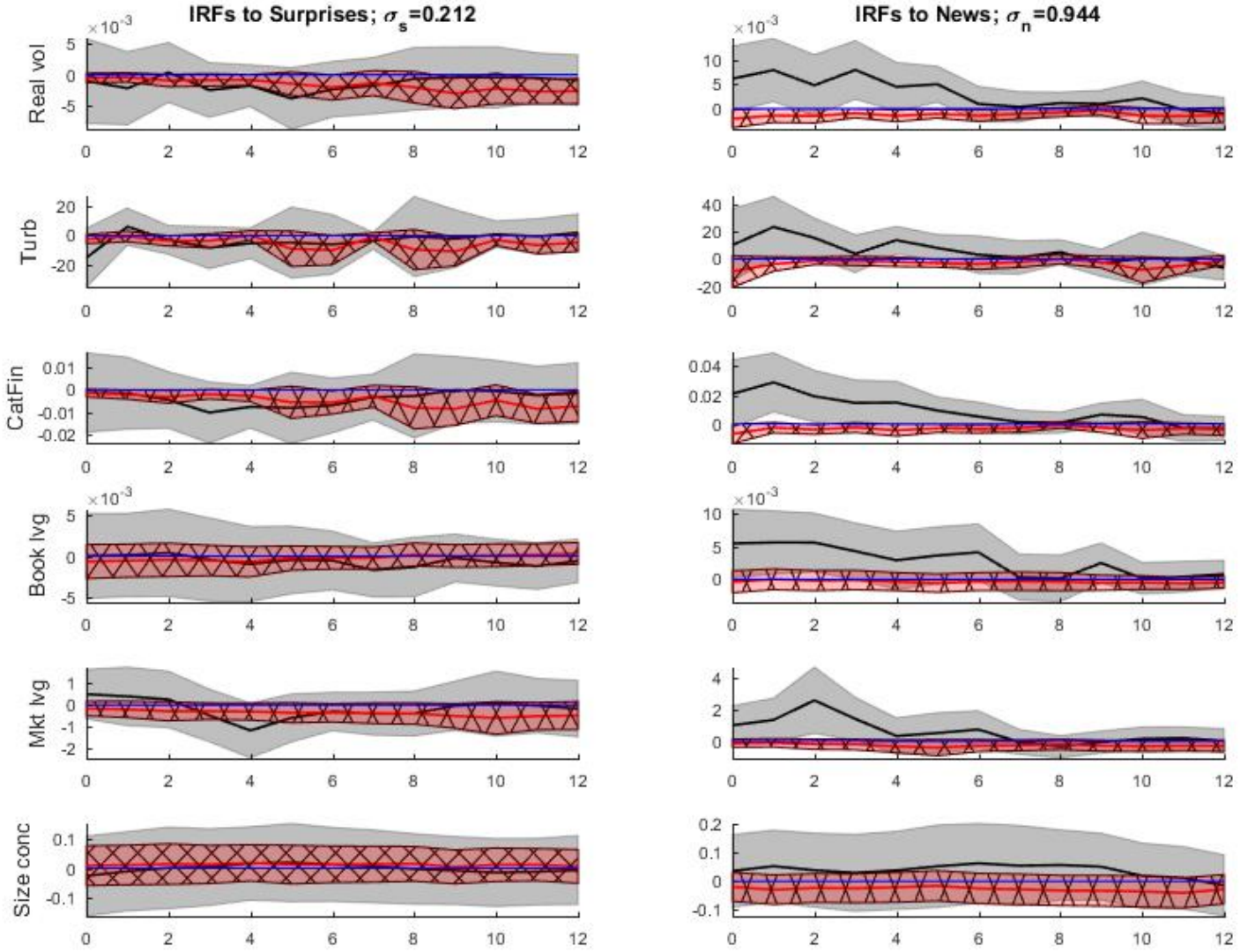


Figure 9: Impulse responses of measures of volatility and instability to one standard deviation of monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals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

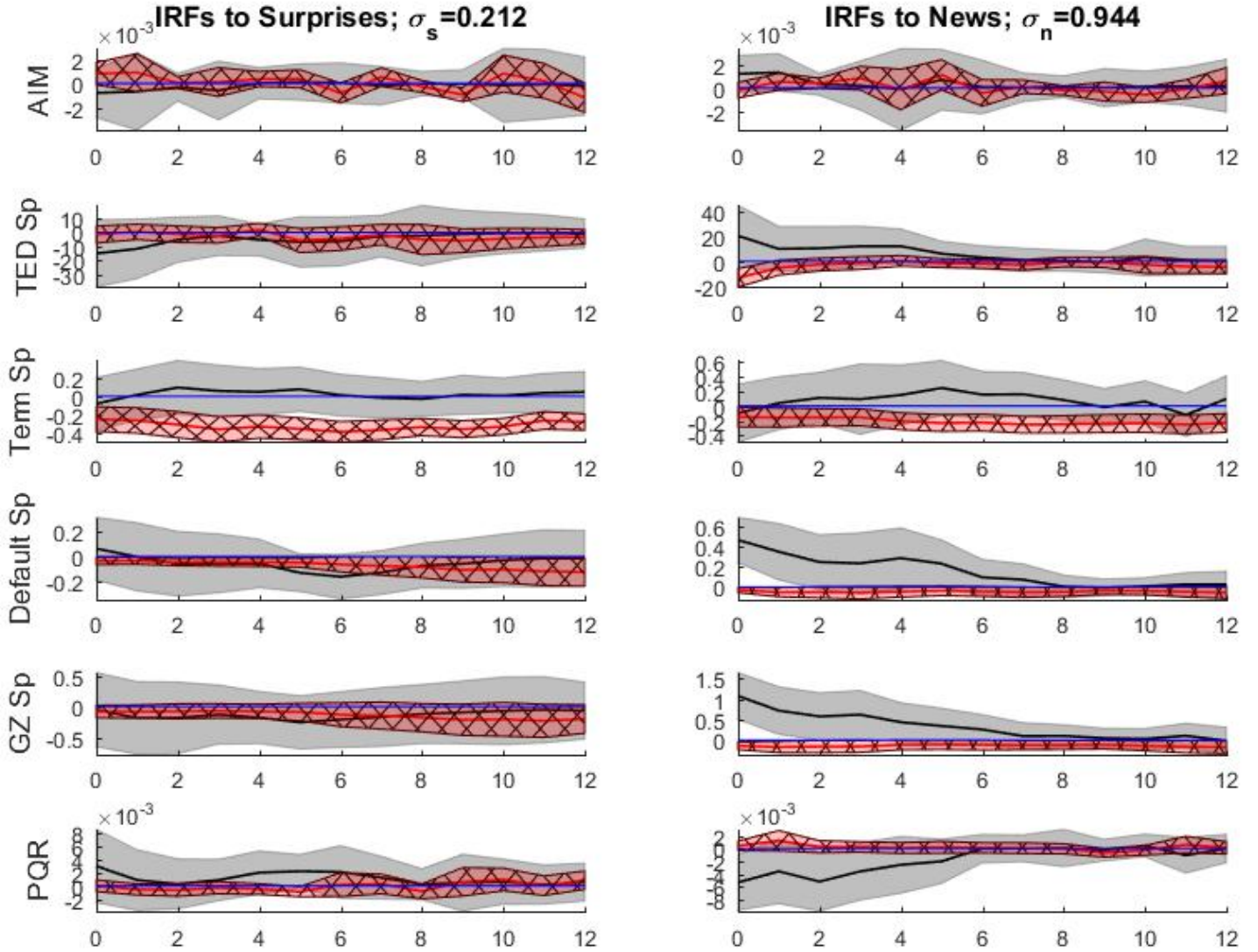


Figure 10: Impulse responses of measures of liquidity and credit to one standard deviation of monetary surprises (left column) and news (right column): black lines and areas—under the ZLB; red lines and (cross-hatched) areas—over the full sample. Newey-West HAC-adjusted 90% confidence intervals are the shaded areas.