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FUTURES-BASED MEASURES OF MONETARY POLICY AND JUMP RISK

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We estimate the effects of anticipated and unanticipated monetary policy changes on jump variation by employing high-frequency nonparametric jump detection methods. We find that anticipated changes in the Fed funds have no significant effect on jumps. In contrast, jump variation in the price of financial market data increases with monetary policy surprises. We document evidence of asymmetries in the response of jumps to monetary policy changes. Monetary policy surprises and positive changes in the Fed target rate induce increments in jumps. Similar results exist in the sector analysis. In addition, this study uncovers no evidence of endogenous response between jumps and monetary policy surprises.

Keywords: Stock Market, Anticipated, Unanticipated, Monetary Policy, Jumps

1. INTRODUCTION

Unanticipated changes in monetary policy and their effects on the equity market are predominant in the literature. The argument is that anticipated policy has no effect on macroeconomic variables. However, early work by Mishkin (1982) shows that anticipated policy can induce changes. Moreover, anticipated exogenous shocks may also be important, as they might reflect the views of private sectors on future policy innovation or central banks' signal for deviation from existing policy.

In this study, we analyze the effects of anticipated and unanticipated monetary policy changes on jump variation. In the first stage, we employ an event study approach to examine the effects of U.S. monetary policy changes on jumps. We analyze the effect of unanticipated (measured at high frequency using Fed funds futures) monetary policy on the aggregate economy and the financial, health, energy, and telecommunication–information technology sectors (Tel-Info).[1] In the second phase, we examine its effect on jumps using unanticipated narrow, wide, and daily measures in a structural VAR framework. This aids us in identifying any

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possible simultaneity or the effects of other macroeconomic variables on jump variation.

Through financial leverage, monetary policy can influence stock returns and volatility as the cost of financing investments through issuing debt changes with changes in the Fed funds [Gospodinov and Jamali (2012)]. In addition, stock volatility and return are forward-looking in nature, and this creates an avenue for instantaneous response to Fed movements. Changes to various short-term interest rates relate closely to changes to Fed funds.[2] Consequently, they may affect the discount rate used in the valuation of different equities' cash flows, and thus a decrease or an increase in volatility and stock returns may be the outcome.

Jumps or discontinuous price changes have become a vital component of financial asset price dynamics. Jumps constitute an important component of equity price changes and possess varying implications for risk and pricing issues. Jiang and Yao (2013) show that illiquid stocks exhibit large discontinuous changes (jumps) and these account for value premia. Through the provision of a persistent and rapidly moving factor that drives conditional return volatilities, jumps constitute a more important issue than jumps in return and diffusive volatilities. Jump detection and applications have continued to evolve over time [examples can be seen in Wang (1995); Carr and Liuren (2003); Johannes (2004); Aït-Sahalia et al. (2005); Barndorff-Nielsen and Shephard, (2006a); Jiang and Oomen (2008); and Lee and Mykland (2008)].

On the importance of jump risk, Tauchen and Zhou (2011) explain that the direct estimation of jump distributions and the identification of realized jumps have important implications for the assessment of financial market risk adjustments. In their conclusion, they argue that more reliable estimation of the jump dynamics is essential for precise quantification of the effect of jump risk premia. With realized jump volatility, they explain that the credit risk premia of Moody's AAA and BAA can be better measured than using the volatility factors (option-implied volatility included) and interest rate factors under appropriate controls for lagged credit spreads and systematic risk factors. They show the high co-movement of the market jump volatility factor with the corporate default rate (65%) and price–dividend ratio (67%). As the impact of a sharp discontinuity in the evolution of prices cannot readily be hedged by a portfolio of underlying cash, assets, and other derivatives, jumps can be of great importance for derivatives pricing and standard arbitrage–based arguments [Bollerslev et al. (2008)]. Thus, jump risk has become an important component in asset pricing. The presence of jumps contributes to incomplete markets and the magnitude of the incompleteness depends on the intensity of jumps and the jump sizes. As revealed by Naik and Lee (1990), the risk of jumps remains important in economies with uncertainty surrounding jump sizes.

Monetary policy is important for jumps in macroeconomic variables. León and Sebestyén (2012) reveal that several jumps in interest rates occurred because of European Central Bank (ECB) unexpected monetary policy decisions, whereas its predictability improved when monetary policy meetings were less frequent.

Fischer and Ranaldo (2011) show that Federal Open Market Committee (FOMC) deliberations cause the trading volume of foreign exchange market to rise by about 5% in the spot and the next spot market day. Examining jumps in the U.S. Treasury market, Jiang et al. (2011) reveal that preannouncement liquidity shocks have significant predictive power for jumps, whereas macroeconomic news announcement surprises have little predictive ability in explaining bond price jumps. Lahaye et al. (2011) relate U.S. macroeconomic news releases to jumps and co-jumps in stock index futures, exchange rates, and bond futures. They reveal that the bond markets are most sensitive to news releases in their study and that announcements on the nonfarm payroll, the Fed funds target, and the gross domestic product are important in all markets.

Although we acknowledge the existing literature, it is fair to state that no empirical work exists to date on jumps and monetary policy changes gauged through the federal funds futures. Our study differs from the existing studies in approach and methodology. We focus on monetary policy as measured through the Fed funds futures and the target rate. Through the federal funds futures, we compute unanticipated monetary policy at various windows. We extract jumps in the stock index through the nonparametric approach of Barndorff-Nielsen and Shephard (2004). Employing the more jump-robust estimator of Andersen et al. (2012), we focus on estimation of the jump variation around the time of monetary policy announcement. More novelty is introduced by estimating jump variation and monetary policy surprises at similar windows. In addition, the present study adds to existing studies on jumps by examining the presence of asymmetries in monetary policy surprises and asymmetries in the target rate.

Whereas existing studies on monetary policy, volatility, and uncertainty in the market concentrate on the aggregate effect, we contribute to the literature by establishing a link between jumps and futures-based measures of Fed policy. We contribute to knowledge by examining this issue at the aggregate and sector levels. In addition, we add to knowledge by revealing the relationship between anticipated and unanticipated monetary policy shocks and jumps. We also show the efficacy of using daily window (event study) methodology (no endogeneity issue) to gauge unanticipated policy changes.

On the difficulty of measuring monetary policy expectations with macroeconomic data releases, Rigobon and Sack (2008) point to the importance of noise in measured data. As rational expectations would incorporate the best forecast, Gürkaynak et al. (2007) provide a justification for using federal funds futures to proxy policy expectation. Among all financial market instruments, the federal funds futures outperform all other securities in forecasting the future path of monetary policy. Gurkaynak et al. (2005) explain and show that market expectation of the Fed funds rate over the month roots from daily changes in the current month futures rate. This study adopts this approach in measuring unanticipated monetary policy surprises.

Researchers have shown that the equity market responds to movements surrounding monetary policy, such as the Federal (Fed) Open Market Committee

Statement and Meeting, leadership changes in the Federal Reserve, and changes in monetary policy direction and stance.[3] Interest rates and stock prices react not only to each other, but also to other economic variables.[4] Using high-frequency data with their inherently heteroskedastic nature, Rigobon and Sack (2004) show that the identification of asset price response to monetary policy changes can be obtained through policy shock variations around the days of (FOMC) meetings and monetary policy testimony to Congress by the chairman. Their results indicate that stock prices fall as short-term interest rates rise.

In macroeconomic issues, monetary policy studies occupy a pillar position. The isolation of unanticipated and anticipated changes in policy and their contributions to equity markets have continued to draw the attention of researchers and policy makers. Researchers have continued to employ different applications and knowledge in pinning down the effect of monetary policy.[5] Unanticipated exogenous shocks to the economy continue to receive much attention in the literature. In congruence with the efficient market hypothesis, Gospodinov and Jamali (2012) show that expected changes of the Fed funds target rate have no significant effect on volatility. In addition, volatility risk premium falls with larger-than-anticipated reductions in the Fed funds rate.

While making decisions, the private sectors take into consideration the possible influences of monetary policy. To maintain the production target, stable and low inflation, central banks also respond to the influence that the decisions of the private sector may exert on the economy.[6]

While examining the response of output to monetary policy news and surprises, as well as their role in the business cycle, Milani and Treadwell (2012) shows that unanticipated policy plays a lesser role than anticipated monetary policy. They point out that a shorter-lived and smaller output response occurs because of surprises from monetary policy. In contrast, a delayed, larger, and more persistent impact occurs from news shock. With a significant contribution of monetary to output fluctuations, based on their specification, 2% of fluctuations emanate from a surprise shock, whereas 15–25% of medium-run output fluctuations occur from anticipated shock.

Past studies that have tried to capture the responsiveness of stock returns, volatility, or other macroeconomic variables to Fed monetary policy changes follow either an event study approach or vector autoregression (VAR) methods, including reduced, identified, and Bayesian forms.[7] In the event study, the assumption is that shocks to the economy do not occur systematically on policy announcement dates. Thus, shocks from monetary policy news are identifiable through the collection of different dates on various events, though contamination by other shocks is a possibility [see, for example, Kuttner (2001) and Bernanke and Kuttner (2005)]. Structural vector autoregressive (SVAR) methodology involves the imposition of certain restrictions on the structural parameter, whereas some studies relax the imposition of exclusion–restriction in the study of monetary policy and stock relationship.[8]

Past studies suggest that the small variance of stock returns is attributable to monetary policy and the response of stock prices comes with a delay. However, financial market theory predicts prompt response of security prices to news. Bjørnland and Leitemo (2009) explain that these results are due to recursive orderings that rule out possible simultaneity. Because the response of asset prices to interest rates might exhibit a complex simultaneous nature, Rigobon and Sack (2003) employ heteroskedasticity of returns to the stock market as an identification method to capture the response of monetary policy instruments to stock market shocks. Their results reveal that monetary policy tightening follows a rise in the equity index. However, recent studies try to solve this simultaneity issue by using a high-frequency observation approach as detailed in our methodology.

The rest of the paper is organized as follows. Section 2 presents the estimation of variances and jumps. Section 3 presents the methodological approach followed. In section 4, the empirical results are given. Section 5 is the conclusion of the study.

2. COMPUTATION OF VARIABLES

In this section, we present a brief discussion on how the variables to be used in the analysis are computed. Specifically, we present the estimation of realized and integrated variances. From these variances, squared jumps in the stock price data will be extracted at high-frequency intervals.

2.1. Estimation of Realized Variance

Within the empirical finance literature, the computation of ex post (historical) volatility from high-frequency data to measure lower-frequency variability is an important tradition. From daily returns, Schwert (1989) and Pagan and Schwert (1990) compute monthly volatility, whereas Taylor and Xu (1997) obtain a daily volatility measure from intraday observation. A computationally simple way to model volatility is attainable with a realized volatility approach. The measurement and application of realized volatility have become achievable with the existence of high-frequency data, even though much noise is present. Over a fixed interval, the sum of finely sampled squared return is commonly used as a measure of realized volatility (nonparametric approach). We follow Barndorff-Nielsen and Shephard (2004), Huang and Tauchen (2005), Barndorff-Nielsen and Shephard (2006b), and Andersen et al. (2007a) to arrive at the definitions of the variables.

In the discrete-time model, the return of an asset is modeled by showing how its value changes from one discrete time to the next. We can represent this process as follows:

$$\text{In}\,(p_t) = \mu + \text{In}(p_{t-1}) + \sigma\varepsilon_t;\ \varepsilon_t \sim \text{i.i.d.}N\,(0, 1) \tag{1}$$

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$\text{In}(p_t)$ follows a random walk process ($\varepsilon_t \sim$ i.i.d.), μ is the drift parameter, p_t is the price of an asset, ε_t is noise, σ is the diffusion parameter, and increments are normal ($\varepsilon_t \sim N$).

With intraday price observations, the realized volatility can be a direct measure of integrated volatility. We define return (R_t) over one day (discrete time) as

$$R_t = \text{In}\,(p_t) - \text{In}(p_{t-1}) = \Delta\text{In}\,(p_t) = \mu + \sigma\varepsilon_t;\, \varepsilon_t \sim \text{i.i.d.}N\,(0, 1)\,. \quad \textbf{(2)}$$

μ generates a drift in $\text{In}\,(p_t)$. With intraday price observations, the estimation of a diffusion process that varies continuously across the day (σ_t) is achievable and the daily return (R_t) is

$$R_t = \text{In}\,(p_t) - \text{In}(p_{t-1}) = \sum_{s=1}^{1/\Delta t} (R_{t-1+s\Delta t}), \quad \textbf{(3)}$$

$$R_{t-1+\Delta t} = \text{In}\,(p_{t-1+\Delta t}) - \text{In}\,(p_{t-1})\,. \quad \textbf{(4)}$$

Δt is a small time interval and in our case this is a 15 minute interval. To obtain a measure of realized variance, we square our continuous return measure:

$$\text{Realized variance}(\text{RV}_t) = \sum_{s=1}^{1/\Delta t} \left(R^2_{t-1+s\Delta t}\right). \quad \textbf{(5)}$$

2.2. Estimation of Realized Bipower Variation/MedRV

Barndorff-Nielsen and Shephard (2004) show that realized bipower variation is robust to jump. Consequently, the estimation of realized volatility or integrated volatility is achievable through the estimation of bipower variation. The strength of bipower variation is that it ensures that jumps (finite activity) do not affect the consistency of the volatility estimate. A significant finite sample jump distortion and the nonallowance for a feasible asymptotic theory under the jump alternative have been criticisms of bipower variation [see Huang and Tauchen (2005); Andersen et al. (2007b); Lee and Mykland (2008)]. Andersen et al. (2012) introduce two new jump-robust estimators of integrated variance—the minimum (MinRV) and the median (MedRV) estimators—to prevail over the bipower and multipower variation measures. Although the MinRV is not particularly efficient, the MedRV enhances efficiency. However, both estimators allow an asymptotic limit theory in the presence of jumps and by using nearest-neighbor truncation, they provide additional robustness to jump and/or microstructure noise (covering both the no-jump null hypothesis and the jump alternative). By using two-sided truncation and picking the median of three adjacent absolute returns, the MedRV achieves a better finite-sample robustness to jumps and the occurrence of zero returns.

The realized variation (RV) is

$$\text{RV}_t = \text{BV}_t + \text{J}, \quad \textbf{(6)}$$

where J = squared jumps on day t and BV = bipower variation,

$$\mathrm{BV}_t = \frac{\pi}{2} \sum_{s=2}^{1/\Delta} |\, R_{t-1+s\Delta t}|\, R_{t-1+(s-1)\Delta t}, \tag{7}$$

where $R_{t-1+(s-1)\Delta t}$ and $R_{t-1+s\Delta t}$ are the contiguous returns over small time intervals. This approximates to integrated volatility in the presence or absence of jumps. We follow this line of literature to estimate the bipower variation as a good measure of integrated volatility. We calculate the return (R_t) and the realized volatility measure and estimate the bipower variation. The difference between the realized variance and the bipower variation (this is also applied to MedRV) is the measure of the jump variation in the price of financial market data:

$$\mathrm{MedRV}_t = \frac{\pi}{6 - 4\sqrt{3} + \pi} \sum_{s=2}^{1/\Delta} \mathrm{med}(|R_{t-1+(s+1)\Delta t}|, |R_{t-1+s\Delta t}|, |R_{t-1+(s-1)\Delta t}|)^2. \tag{8}$$

The estimation involves taking and squaring the median absolute return among the three consecutive returns. We calculate the jumps after obtaining our estimates of bipower variation/MedRV and realized variance. Jumps estimated using bipower variation will retain the name "jump," whereas jumps estimated using MedRV will be referred to as "jump-robust."

2.3. Estimating Jumps

Volatility modeling remains pivotal in risk management, asset pricing, and allocation and in other macroeconomics-related issues such as fiscal and monetary policy decisions. In assessing the daily distributive properties of return in continuous-time jump diffusion models, Andersen et al. (2010) identify the importance of analyzing stock price dynamics in such a manner that time-varying jumps, diffusive volatility, and leverage effects are allowed to describe these dynamics. In their construction of a leverage and jump test, they reveal that realized measures of variance and high-frequency intraday data can be used to accomplish this purpose. Jiang and Oomen (2008) develop jump detection test when asset prices are observed with noise. In this study, we follow the standard basic jump detection technique of Barndorff-Nielsen and Shephard (2004) in estimating small and large changes in asset prices over minute periods.[9] For more accurate jump detection, we employ the MedRV.

The presence of jumps in the return process hinders realized volatility from approximating to the true integrated variance, as the sum of squared jumps on a day is included in the realized variance. In this case, we make use of realized variance (RV) and bipower variation,

$$\mathrm{RV}_t - \mathrm{BV}_t = \mathrm{J}, \tag{9}$$

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where jump (J) = the difference between realized volatility and bipower variation:

$$J_{1,1:T} = \sum_{t=1}^{T} \mathrm{RV}_t - \sum_{t=1}^{T} \mathrm{BV}_t. \qquad (10)$$

We calculate jumps from our estimated realized variance and bipower variation. To obtain jumps at a tight window, we calculate the high-frequency realized variance and bipower variation and obtain our jumps for each 15 minute interval. In the second case, we repeat the process using realized variance and the MedRV. Using the announcement time, we obtain the jump variation at each of the three windows surrounding the announcement (see Section 3).

3. METHODOLOGICAL PROCEDURES

3.1. Monetary Policy Surprise and Jump Estimation from High-Frequency Data

An alternative measure of monetary policy surprise proposed by Gurkaynak et al. (2005) allows changes in futures prices around the policy announcement to represent unanticipated monetary policy surprise. They state that the expectation of a future Fed funds rate (Fed fund futures contract) rather than the changes in the Fed funds target rate would be the measure of unanticipated policy for the financial markets.[10] They explain and show that market expectation of the Fed funds rate over the month roots from daily changes in the current month futures rate. Therefore, we compute unanticipated changes of monetary policy with the federal fund futures rate. In this section, we estimate unanticipated and anticipated policy changes.

We follow this methodological approach in arriving at our measure of monetary policy surprise. We construct changes in the Federal futures fund in daily, one hour, and thirty minute windows surrounding FOMC announcements from 2002 to 2013. We use the time on press releases after the meeting by the FOMC. We use intraday data to capture the changes of Federal funds one-month futures surrounding the announcements. This allows the estimation of monetary policy free from contamination from other economic news releases.

We measure policy surprise in this section by using a one-dimensional policy methodology that exists in the literature [see Gurkaynak et al. (2005)]. To capture jump responses to unanticipated Fed action, we estimate the jump variation on the days of the announcement in daily, one hour (wide), and thirty minute (narrow) windows. This allows us to estimate the effect without issues of endogeneity (for narrower windows) or other news effect on jump. The regression is

$$\Delta \mathrm{jp}_t = \alpha + \beta \Delta \mathrm{UM}_t + \varepsilon_t, \qquad (11)$$

$$\Delta \mathrm{jp}_t \equiv \mathrm{jp}_t - \mathrm{jp}_{t-1}, \qquad (12)$$

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where Δjp_t = the jump around the time of the announcement, $\text{jp}_t = \text{RV}_t - \text{BV}_t$, ΔUM_t is the unanticipated monetary policy component, and ε_t is the stochastic news term. We then estimate the preceding equation as a high-frequency event-study analysis. Robust standard errors are obtained for a valid inference when there is any departure from the assumption that the error term in equation (11) is i.i.d.

Due to omitted variables and simultaneous equations issues, estimation on a monthly or quarterly basis in the case of asset study is circuitous unless these issues are resolved [Gurkaynak et al. (2005)]. This could mean that a change in monetary policy is a response to changes in asset prices in previous months or quarters or even on previous days. It could also be seen that changes in realized volatility (which harbors jumps) and Fed policy changes are due to macroeconomic news as embedded in the residual component. Consequently, the violation of orthogonal residual is unavoidable in the latter case, but these issues may be avoidable in the case of higher-frequency analysis. However, Bernanke and Kuttner (2005) argue that even at such a high frequency, simultaneous equations issues are still viable, because changes to FOMC target rate come after and/or in response to the release of employment reports by the Bureau of Labor Statistics. Thus, daily data to an extent still harbor endogenous responses. To address this issue, Gurkaynak et al. (2005) suggest the estimation of the event study in a narrow window for bot the explanatory variable and the explained variable. The shrinking of the window time to an hour or less makes it less likely that other events have significant play in the estimation of the equation. Bracketing the announcement time allows the exclusion of Fed response to equity prices and helps to solve the issue of omitted variable bias. In addition, Rosa (2011) shows that the event study methodology is preferable to a heteroskedasticity-based estimator. To estimate our jump variation, we follow this line of approach. Similarly to existing literature such as Bernanke and Kuttner (2005) and Gospodinov and Jamali (2012), we compute actual changes to Fed funds target rate and obtain the expected changes as

$$\bar{\Delta} i^a = \bar{\Delta} i - \bar{\Delta} i^u, \tag{13}$$

where $\bar{\Delta} i^a$ = anticipated monetary policy change, $\bar{\Delta} i$ = changes in Fed funds target rate, and $\bar{\Delta} i^u$ is the unanticipated monetary policy change (we employ our daily window measure of monetary policy surprise explained earlier).

3.2. Data Description

The data on FOMC meeting days are from the Website of the Board of Governors of the Federal Reserve System. We obtain federal funds futures one-month contract tick-by-tick data from 2002 to 2013. The data are sourced from the Securities Industry Research Centre of Asia Pacific (Sirca), and for our daily window, we employ Bloomberg data. To estimate jumps, we obtain intraday (15 minute) stock prices from the Sirca database and calculate both bipower variation and realized variance. The 15 minute sampling frequency has good jump detection power [Lee and Mykland (2008); Lahaye et al. (2011)]. We then extract our jump measure at each 15 minute interval. We estimate our values from the S&P500 stock index and from S&P 500 sector indexes [financial sector index, health sector index, energy sector index, and telecommunication and information technology sector index (Tel-Info)]. We source the Federal funds target rate, the Institute for Supply Management (ISM) index, and employment (nonfarm payroll) and industrial production data from DataStream.

3.3. Structural VAR

Most time series analyses of the relationship between policy and economic variables have relied on vector autoregressive models (VAR) since the seminal paper of Sims (1980). In this method, reduced form errors relate to the structural innovation through identifying assumptions. Variant approaches exist, but short- and long-run restrictions dominate in the literature. The imposition of short-run restrictions implies that some structural innovations do not contemporaneously affect some variables in the system.

In this section, we analyze the effect of policy changes on jumps by following a structural VAR approach. Apart from the least-squares regressions of event study methodology, we estimate orthogonal structural impulse responses of jumps due to unanticipated monetary policy. We examine possible simultaneity in jump response to monetary policy changes at the narrow, wide, and daily windows. In this section, we employ structural vector autoregressive (VAR) bivariate and multivariate models. We restrict our estimation of the short run effect of monetary policy. In the bivariate case, we order our variables recursively so that the vector of variables $S_t = [M_t, J_t]$. The variables are unanticipated monetary policy M_t, and jump J_t. By this ordering, unanticipated monetary policy affects jumps contemporaneously whereas jumps affect monetary policy with a lag. Thus, we consider the potential endogeneity of unanticipated monetary shocks.

The structural form equation is

$$C\,(L)\,S_t = \varepsilon_t, \tag{14}$$

where $C\,(L)$ is a matrix polynomial in the lag operator L, S_t is an $n \times 1$ data vector, and ε_t represents an $n \times 1$ vector of serially uncorrelated structural shocks. $\text{var}(\varepsilon_t) = I$ and I is a diagonal matrix where the diagonal elements are the variances of the structural disturbances; thus, structural disturbances are assumed to be mutually uncorrelated. The structural parameters and the residuals able to be estimated; the reduced-form VAR is needed and can be estimated to identify the structural parameters,

$$S_t = B(L)S_t + e_t, \tag{15}$$

where $B(L)$ is a matrix polynomial without a constant term in the lag operator L, e_t is an $n \times 1$ vector of reduced-form residuals, $\text{var}(e_t) = \Sigma$, and $B\,(L)$ is

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invertible. The reduced-form errors (e_t) are linear combinations of the structural errors $(\varepsilon_t).\varepsilon_t = C_0 e_t$. We denote the contemporaneous matrix of the structural form by C_0 and $\widetilde{C}$ as the coefficient matrix in $C(L)$ without $C_0(C\,(L) = C_0 + \widetilde{C}\,(L))$ and $B\,(L) = -C_0^{-1}\widetilde{C}\,(L)$. The contemporaneous relationship among variables in the reduced-form VAR model hides in the variance/covariance matrix [Amisano and Giannini (1997)]. Structural VAR estimation necessitates the recovery of the hidden contemporaneous information for an orthogonal residual impulse response analysis. In relation to the Sims (1980) Cholesky decomposition of the variance/covariance matrix, we will require $n(n-1)/2$ additional restrictions to achieve exact identification. In a bivariate model, this translates to one additional restriction on the contemporaneous matrix for exact identification (the standard Cholesky decomposition of the estimate of the variance/covariance matrix is employed so that unanticipated monetary policy is not contemporaneously affected by jumps).

4. RESULTS

4.1. Jump Responses at Various Windows

We test for unit root using augmented Dickey–Fuller and Phillips–Perron tests, and as expected, all the variables (jump, anticipated, and unanticipated policy measures) are stationary at level (I (0) variables). We also undertake a robust examination of our analysis. In this section, we present the results of the event study methodology. The dependent variable is the jump variation in each of the three windows, whereas the independent variable is the change in the Federal funds futures rate in each of the three windows.

The results of jumps measured at the daily window, which Table 1 presents, reveal that Federal funds surprises significantly affect jumps. The results from both measures of jumps are consistent. However, we will use the "jump-robust" results in the interpretation. Unexpected change in Fed action leads to an increment in jumps. A look at the market reaction to unexpected policy action reveals increments in jumps in all windows. The increase in market jumps has the highest coefficient (0.0174) for the narrow monetary window measure. Looking at sector responses, similar results are obtained. An unexpected policy change induces increases in sector jumps. Jumps in the energy sector have the highest reaction to the wide-monetary-window measure (0.0347). Tel-Info has its highest response to Fed policy changes in the narrow window, with a 0.0168 percentage point increment, whereas the financial sector responds significantly when "jump" is used. The health sector shows a significant increment (0.0157 as the maximum) in jumps for all monetary-window measures. In these windows, the responses of jumps to Fed actions reveal that the narrow monetary window produces a stronger response than other window measures. In this specification, the greatest increment in jumps due to unexpected monetary actions is recorded in the energy sector.

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TABLE 1. Market and sector responses of jumps to Federal funds surprises

Window	Market	Energy	Tel–info	Finance	Health	Jump type
Daily	0.0014***	0.0031***				1
	(0.0005)	(0.0009)				
	0.0019***	0.0030***	0.0017**		0.0017***	2
	(0.0006)	(0.0009)	(0.0007)		(0.0004)	
Wide	0.0136***	0.0328***	0.0125***		0.0044**	1
	(0.0032)	(0.0056)	(0.0039)		(0.0017)	
	0.0185***	0.0347***	0.0129***		0.0150***	2
	(0.0036)	(0.0055)	(0.0043)		(0.0024)	
Narrow	0.0146***	0.0293***	0.0157***	0.0032**		1
	(0.0037)	(0.0068)	(0.0043)	(0.0015)		
	0.0174***	0.0313***	0.0168***		0.0157***	2
	(0.0043)	(0.0068)	(0.0048)		(0.0028)	
Observations	94	94	94	94	94	

Notes: Window represents the monetary surprise measure. Wide = 1 hour; Narrow = 30 minutes. Standard errors in parentheses. 1 represents "jump" and 2 represents "jump-robust," and these are measured at the daily window. The financial sector is winsorised at the narrow window.
*** $p < 0.01$. ** $p < 0.05$.

The results, as shown in this study, partially receive support from similar studies on the response of disaggregated indexes to monetary policy. Bernanke and Kuttner (2005) reveal that the stock returns of telecommunications and high-tech industries are most responsive to monetary policy, having a coefficient twice that of the overall value-weighted index, whereas energy and utilities are only half as responsive as the overall market, with insignificant coefficients. They link this to the market betas of the associated industries. Researchers have offered possible explanations for why stock return across industries might react differently to monetary policy shocks. For capital-intensive industries, the cost of capital induced by monetary policy becomes important, whereas tradable goods industries will be affected when monetary policy affects the exchange rate. From the credit channel of monetary policy, the response of firms to monetary policy tends to be asymmetric. Firms in financial constraint will be more responsive to changes in interest rate, whereas the size of a firm is a possible determinant of the firm's response to changes in monetary policy [see, for example, Thorbecke (1997); Ehrmann and Fratzscher (2004)]. Although beyond the scope of this study, the observed high jumps in the energy sector could be linked to these factors. In the remaining analysis, the "jump-robust" measure will be used.

In Table 2, we present the results of wide and narrow window surprise policy measures against jumps measured in wide and narrow windows. The significance of the coefficients for the energy and telecommunication–information sectors is maintained. We find an increase in the response of the energy sector jumps

TABLE 2. Responses of sector jumps to Federal funds surprises

Window	Energy	Energy	Energy	Tel–info	Tel–info	Tel–info
Wide	0.0204***			0.0149***		
	(0.0038)			(0.0038)		
Narrow		0.0270***	0.0266***		0.0192***	0.0186***
		(0.0040)	(0.0042)		(0.0042)	(0.0043)
Observations	94	94	94	94	94	
Window	Wide	Wide	Narrow	Wide	Wide	Narrow

Notes: The vertical window represents surprises in monetary policy whereas the horizontal window represents jumps measured in these windows. Standard errors in parentheses. Wide = 1 hour and narrow = 30 minutes.
*** $p < 0.01$.

in the wide window. In addition, narrow window jumps in the energy sector significantly respond to the narrow window monetary policy surprise measure. In the telecommunication–information technology sector, the wide window jump responds to narrow and wide window monetary policy changes and the narrow window jump responds to narrow window monetary policy surprises. In this specification, the narrow window jump in the energy sector exhibits a larger response to unexpected policy shocks.

In Table 3, we examine the robustness of our daily window jump measure against monetary policy surprises. The result reveals that the market, energy, health, and telecommunication–information representations are robust to autocorrelation and heteroskedastic issues. Specifically, in the market, health, and energy representations, the wide window monetary policy measure produces a robust estimate, whereas the telecommunication–information technology representation is robust in the wide jump window. A further robustness check is undertaken by dividing the sample into different periods to include pre-crisis (2002–2006), crisis (2007–2009), and post-crisis (2010–2013). Given that quantitative easing has been invoked since the end of the 2008 financial crisis, we further separate the sample into two periods to cover conventional (2002–2008) and unconventional (2008–2013) policy periods. The results reveal that jumps respond to monetary policy surprises. Jumps show the greatest response during the financial crisis period, whereas a significant but smaller effect is recorded prior to the crisis. A look at the conventional monetary policy period shows that jumps respond to monetary policy surprises (0.0163).

Previous studies on stock returns [Bernanke and Kuttner (2005)] indicate that unanticipated policy changes lead to a decline in stock returns, and studies on volatilities [Gospodinov and Jamali (2012)] indicate that volatility increases with surprise components of Fed actions. Our result helps confirm previous findings. As volatility increases with surprise monetary policy, we show that the possibility of such results might stem from a positive jump response to Fed surprises, because volatility increases with an increase in jumps. In addition, a decrease in stock returns depicts higher volatility because of the negative correlation between

TABLE 3. Robustness of jumps measured in the daily window

Window	Market	Energy	Health	Tel–info	
Wide	0.0185**	0.0347**	0.0150**		
	(0.0073)	(0.0148)	(0.0073)		
Narrow				0.0192*	
				(0.0114)	
Observations	94	94	94	94	
			Market		
	2002–2006	2007–2009	2010–2013	2002–2008	2009–2013
Wide	0.0019**	0.0256***	0.1496**	0.0163**	0.1265*
	(0.0008)	(0.0029)	(0.0653)	(0.0070)	(0.0639)
Observations	35	29	30	56	38

Notes: Robust standard errors in parentheses. Window represents the monetary surprise measure. Daily jump window is used except for tel–info (wide window).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

volatility and stock returns, as supported in previous studies [see, for example, Black (1976)]. However, a change in the timing of volatility and stock returns can alter this relationship [see, for example, Bollerslev et al. (2006)].

4.2. Jump Responses to Anticipated and Unanticipated Fed Surprises

To examine the responses of jumps to expected and unexpected Fed surprises, we employ the daily jump window against wide window monetary surprise calibration. To achieve this objective, we estimate changes in the Fund target rate and apply the formula as given in equation (13) to obtain the anticipated policy change. We implement the specifications stated in the following equation:

$$\Delta jp_t = \alpha + \beta_1 \bar{\Delta} i_t^a + \beta_2 \bar{\Delta} i_t^u + \beta_3 \bar{\Delta} i_t + \varepsilon_t. \quad \textbf{(16)}$$

The results of the specification presented in Table 4 reveal that unexpected Fed policy changes increase jumps. The results are statistically and economically significant for the aggregate representation as well as sector representations. Consistent with the efficient market hypothesis, policy changes that are anticipated have no significant effect on jumps. This entails that jumps follow the arrival of new monetary information. The jump in the energy sector has the highest coefficient. In contrast to unanticipated policy changes, changes in the Fed target rate have no effect on jumps, similarly to anticipated policy changes. This supports the idea of capturing monetary policy surprises with the Fed futures rate and not the target rate itself.

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TABLE 4. Jump response to monetary policy changes

	Market	Energy	Tel–info
Anticipated change	−0.0001	−0.0013	−0.0010
	(0.0001)	(0.0009)	(0.0007)
Unanticipated change	0.0172***	0.0299***	0.0082*
	(0.0038)	(0.0058)	(0.0045)
Target rate change		0.0010	0.0006
		(0.0009)	(0.0007)
Observations	94	94	94

Notes: We measure unanticipated monetary policy using the wide window in this panel. Standard errors in parentheses.
*** $p < 0.01$, * $p < 0.1$.

4.3. Jump Response and Asymmetries

In regard to asymmetries, Bernanke and Kuttner (2005) identify that stock returns respond to the direction of monetary policy changes in the daily surprise measure. At the intradaily level, asymmetric equity response to monetary and macroeconomic news exists [see, for example, Andersen et al. (2003); Chuliá et al. (2010)][11]. The direction of Fed action might constitute a major decision element for equity market participants. Gospodinov and Jamali (2012) uncover an asymmetric response of volatility to Fed funds actions. Increases in interest rates may constitute bad news to the stock market. Thus, the direction of policy action will affect the sign of equity and macroeconomic responses. To account for the direction of policy changes, we employ an interactive dummy variable (negative surprise multiplied by a dummy that takes a value of 1 for negative surprises and 0 otherwise (positive or no change). We implement this using daily window monetary policy surprises (negative surprise) and the opposite is implemented for changes in the Fed target rate (positive surprise). The presence of asymmetric response to policy changes is visible in Tables 5 and 6.

TABLE 5. Asymmetries of jump response to monetary policy changes

	Market	Energy	Health
Expected change	0.0001	−0.0000	−0.0000
	(0.0001)	(0.0002)	(0.0001)
Unexpected change	0.0042***	0.0075***	0.0043***
	(0.0014)	(0.0022)	(0.0008)
Negative unexpected change	−0.0034**	−0.0072***	−0.0042***
	(0.0016)	(0.0025)	(0.0009)
Observations	94	94	94

Notes: We employ daily changes in jumps and monetary policy in this specification. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$.

TABLE 6. Asymmetries of jump response to target rate changes

	Market	Energy	Health
Target rate change	−0.0005**	−0.0012***	−0.0008***
	(0.0002)	(0.0004)	(0.0001)
Positive target rate change	0.0011*	0.0026**	0.0016***
	(0.0007)	(0.0012)	(0.0005)
Observations	26	26	26

Notes: We employ daily changes in jumps and monetary policy in this specification. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$.

The results reveal asymmetries in the response of jumps to surprise actions. Specifically, an unexpected change that is negative induces a fall in jumps. This shows that a contractionary monetary policy leads to more jumps. This observation strengthens our preceding findings and supports previous related and relevant studies on Fed policies. A similar observation applies when direction of changes in the target rate is used to account for asymmetries. In Table 6, we show that positive changes in the target rate itself significantly affect the direction of response. Equity holders are alert to Fed policy responses to equity prices. The Fed funds rate, which is the interest rate for trading of Fed funds by depository institutions, remains an important Federal Reserve monetary policy transmission link to other interest rates. Its effectiveness as a monetary policy tool continues to draw more and more studies on responses of economic variables, the stock market, and agents to its changes. By separating target funds rate changes into unanticipated and anticipated components, Kuttner (2001) reveals that unanticipated changes in target rate causes a significant interest rate response, whereas anticipated changes produce a small effect. As confirmed by the results, an increase in the interest rate generates an increase in jumps.

4.4. Testing for Simultaneous and Endogenous Dimensions of Jump Response

At lower frequency, event study might suffer from omitted-variable and simultaneous equations issues. This could mean that a change in monetary policy is a response to changes in previous periods. As macroeconomic news could influence volatility, jumps, and Fed policy changes, the violation of orthogonal residuals is possible. Endogenous responses might still be present at daily frequency study, as Bernanke and Kuttner (2005) argue that simultaneous equations issues are still viable, because changes in the FOMC target rate comes after and/or in response to the release of employment reports from the Bureau of Labor Statistics.

To account for the possible influence of other macroeconomic variables and for endogenous response in the daily window observation, we employ the SVAR approach in this section. First, we run a bivariate model involving the three-window measures of unanticipated monetary policy changes and jumps measured at the daily window. These are estimated at lags 1, 2, and 2, variables are stationary, and the system is stable. In the second phase, a multivariate model involving macroeconomic variables and a daily window measure of unanticipated monetary policy shock is tested. Each of the macroeconomic variables is logged and differenced. These are estimated at lags 1, 2, and 2 for specifications involving (industrial production, monetary policy, jumps), (employment, monetary policy, jumps), and (ISM index, monetary policy, jumps) respectively (see Figure 1). These variables are common in monetary policy studies [see, for example, Gospodinov and Jamali (2012)].

The results in Figure 2 reveal no possible endogenous response between monetary policy changes and jumps for either low- or high-frequency measurements. All jumps increase with unanticipated policy shock and die out at 2–3 lags. Some studies point to a bidirectional relationship between the stock market and monetary policy variables. To achieve identification without an exclusion restriction issue, D'Amico and Farka (2011) use high-frequency data in combination with a VAR approach to examine the relationship of monetary policy to the stock market. They find that tightening of Fed policy rates negatively affects stock prices, whereas a significant response of the Fed to stock market movements exists. Given the importance of the equity market in an economy, the role of the equity market in monetary policy decision making cannot be overlooked. Through changes to the financial wealth of households and investors, the stock market affects the economy, whereas changes in expected earnings and interest rates through policy decisions may influence equity prices. In our case, jumps are insignificant fort monetary policy actions, even in the daily window measure.

Figure 1 presents the results of examination of the impacts of macroeconomic variables on the daily window jump measure. Similarly to the results in Figure 2, macroeconomic variables are insignificant to affect jumps in the daily window measure. Though a similar pattern of response to shock in monetary and macroeconomic variables is observed, industrial production, employment, and the ISM index do not affect jumps in the daily window observation. This suggests that the daily window event study approach still represents a valid economic analysis.

5. CONCLUSION

With event study and SVAR methods, this paper provides the first characterization of the linkage between jumps and monetary policy changes. Using Federal funds futures to capture market expectations for monetary policy, we investigate the response of jumps to expected and unexpected policy changes. Across a variety of specifications, we document a strong and consistent response of jumps to unexpected Fed policy changes. There is significant evidence that expected policy changes do not affect jumps. Our results suggest that jumps soar with positive unanticipated policy change. The results on the effect of the Fed target rate suggest that positive changes in the Fed target rate induce more jumps. The responses of

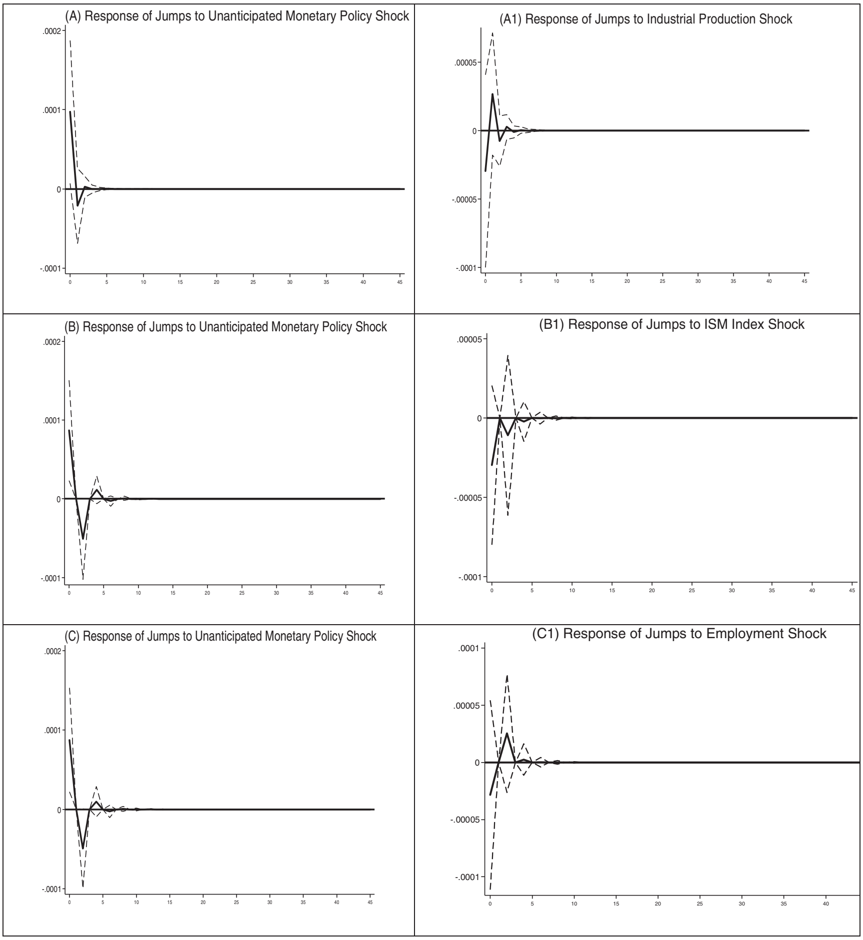

FIGURE 1. The impulse response of daily window jumps and daily window unanticipated monetary policy change, industrial production, ISM index, and employment. The dashed lines are 90% bootstrapped confidence intervals with 500 replications. The vertical column represents coefficients, whereas the horizontal line is the time horizon.

jumps in the various sectors are similar to the aggregate results. In our analysis, jumps in the energy sector tend to react most to policy changes. Introducing macroeconomic variables and using SVAR to solve for endogenous responses and possible influences of other macroeconomic variables reveals that the daily window measure is robust to endogenous issues and macroeconomic influences.

As an increase in the interest rate depicts an increase in interest cost, which induces stock riskiness and volatility, there is a possibility that increases in volatility stem from these increases in the jump variation of the stock market data. Using features-based measures of monetary policy, we document evidence of

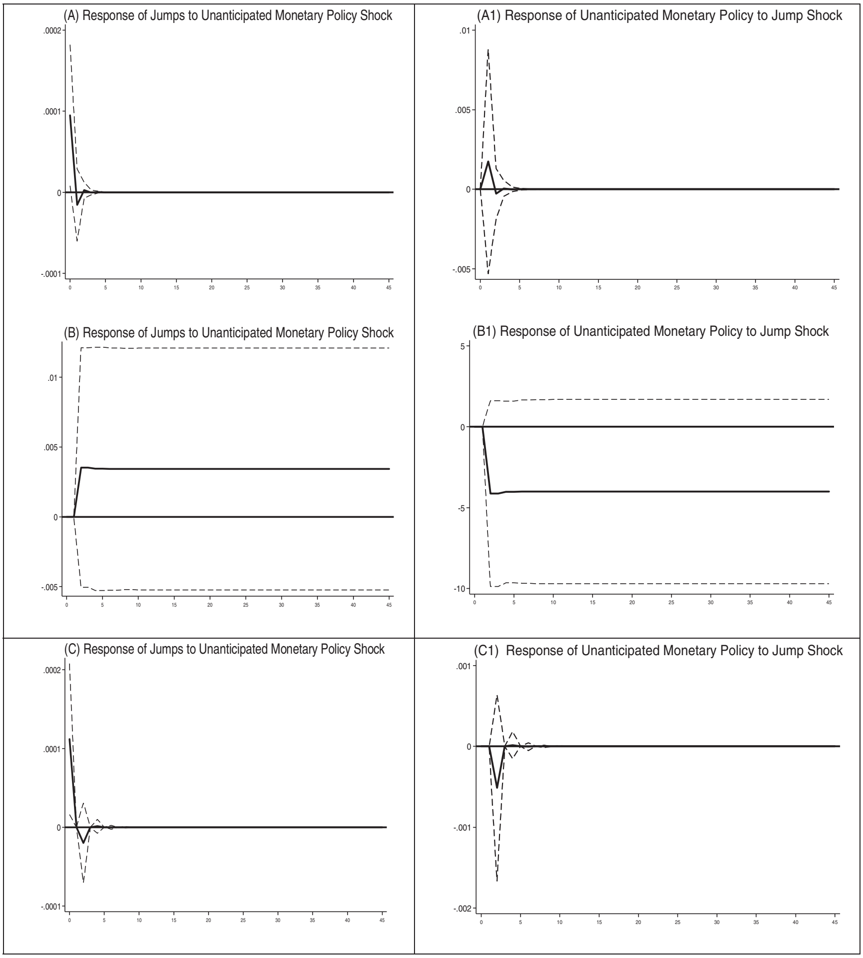

FIGURE 2. The impulse response of jumps and unanticipated monetary policy (MP) changes: A = daily window MP, B = wide window MP, C = narrow window MP. A1, B1, and C1 are daily window jumps. The dashed lines are 90% bootstrapped confidence intervals with 500 replications. The vertical column represents coefficients, whereas the horizontal line is the time horizon.

asymmetric response of jumps to unanticipated policy changes. Thus, this study strengthens previous studies by further revealing the relationship between monetary policy and the stock market. More importantly, as jumps have become of great importance in derivatives pricing and standard arbitrage-based arguments, we reveal that positive unanticipated monetary surprises and target rate changes induce increments in jump-type market fluctuation. By increasing jumps, unanticipated monetary policy has important implications for the assessment of financial market risk adjustments, whereas anticipated policy change does not. These results remain immune to various jump identification approaches, sampling periods, and conventional and unconventional monetary policy periods.

NOTES

1. These sectors have high-frequency stock index data.
2. To capture time series facts of the U.S. economy, Bernanke et al. (1997) show that the depressing impact of oil price shocks is linked to endogenous monetary policy response.
3. Examples include but not limited to Bernanke et al. (1997) and Gurkaynak et al. (2005).
4. Eickmeier and Hofmann (2013) relate monetary policy to housing booms, whereas Dai and Spyromitros (2012) examine optimal monetary policy with asset price included in a macroeconomic model. Other studies that relate monetary policy to asset prices, recession, and inflation risk include Sims and Zha (2006), Gavin et al. (2009), and Pfajfar and Santoro (2014).
5. From the maturity structure of the yield curve, Claus and Dungey (2012) show that different shocks from monetary policy yield differing responses, as opposed to the view that same policy shock induces different responses by the term structure.
6. To solve for the simultaneity issue, Bjørnland and Leitemo (2009) impose both short- and long-run restrictions and reveal a huge interdependency between real stock prices and setting of U.S. interest rates.
7. To estimate the impact of monetary policy shocks through a Bayesian approach, Uhlig (2005) imposes sign restrictions on the impulse responses of nonborrowed reserves, prices, and the federal funds rate in response to a monetary policy shock.
8. D'Amico and Farka (2011) develop a new procedure to overcome exclusion restriction. They show that monetary policy tightening induces a negative stock response, whereas stock price movements induce Federal Reserve action.
9. This is calculated with over 82,000 observations for each sector and for the market representation at each 15- minute interval; therefore small sample bias is not an issue in this case.
10. Using high-frequency event-study analysis, Gurkaynak et al. (2005) examine U.S. monetary policy impacts on asset prices. They estimate changes in the prices of assets by using data that measure these reactions in one hour and thirty minutes windows surrounding the FOMC announcement (communication of policy decision to financial markets). They argue that the use of intraday data helps to capture asset price response to monetary policy exclusively, as no other economic news is invoked within this time interval. They reveal that both monetary policy statements and actions importantly but differently affect the prices of assets.
11. Fielding and Shields (2011) uncover an asymmetric response of the real exchange rate to federal monetary policy shocks.

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