When Does the Fed Care About Stock Prices?

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Abstract

We propose a novel identification approach based on a predictable change in the intraday volatility of index futures to estimate the Federal Reserve's reaction to stock returns. This identification approach relies on a weaker set of assumptions than required under identification through heteroskedasticity based on lower frequency data. Our approach also allows the examination of changes in the reaction of monetary policy to the stock market. We document an asymmetric response of policy expectations to changes in stock prices in adverse and positive economic environments. Specifically, the results show a sharp increase in the response of monetary policy expectations to stock returns during recessions and bear markets. This finding is consistent with the existence of the so-called "Fed put."

JEL classification: E44; E52; E58; G14; G18

Keywords: Monetary policy; Stock market; Intraday data; Futures; Identification; Heteroskedasticity

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"Let me be clear, there is no Fed equity market put. … We do not care about the level of equity prices, or bond yields or credit spreads per se. Instead, we focus on how financial market conditions influence the transmission of monetary policy to the real economy."

William C. Dudley, President and CEO of the Federal Reserve Bank of New York,
Remarks at Baruch College, December 1, 2014

"Fed officials can confidently say what Dudley said when equities are at record highs. I would take them more seriously if they say things like this in the midst of a 10 percent sell-off in equities."

Hedge fund manager Stephen Jen of SLJ Macro Partners, December 2014
Quoted at http://blogs.reuters.com/james-saft

"Global stock-market turmoil has weakened the case for raising interest rates in September, Federal Reserve Bank of New York President William C. Dudley said. … "From my perspective, at this moment, the decision to begin the normalization process at the September FOMC meeting seems less compelling to me than it was a few weeks ago," Dudley told a news conference Wednesday at the New York Fed."[1]

Bloomberg, August 26, 2015

1. Introduction

Many investors believe that the Federal Reserve will rescue financial markets in periods of market stress. The Fed's pattern of easing monetary policy in reaction to market declines is known as the "Fed put," sometimes named after the current Fed chairperson, such as the "Greenspan put" or, more recently, the "Powell put." However, bear markets often coincide with recessions and the "Fed put" could be coincidental with actual Federal Reserve (Fed) policy aimed at stabilizing employment and inflation rather than financial markets (e.g., Poole, 2008). Cieslak and Vissing-Jorgensen (2021) argue that the Fed's reaction to the stock market may be justified if the equity market downturn predicts falling consumption or lower future investment.[2]

[1] The news conference at which Mr. Dudley made the quoted remarks was held after the S&P 500 index fell by about 11 percent in five trading days. In the hours following his remarks, the S&P 500 increased by about 3 percent.
[2] For example, when the Federal Open Market Committee (FOMC) held an unscheduled conference call on January 21, 2008, Fed Chairman Ben Bernanke said in his initial remarks: "... the S&P 500 was off about 60 points today, close to 5 percent. That makes the cumulative decline in the S&P 500 since our last FOMC meeting 16½ percent. Obviously, it is not our job to target stock values or to protect stock investors, but I think that this is a symptom of both sharply mounting concerns about the economy and increasing problems in credit markets. On the economy, the data and the information that we can glean from financial markets reflect a growing belief that the United States is in for a deep and protracted recession." (Transcript of January 21, 2008 conference call, page 6.)

Understanding the link between monetary policy and the stock market is critical for monetary policy makers because of the macroeconomic consequences of wealth effects that result from large changes in asset prices. Obviously, the link is also important for investors who keep a close watch on monetary policy. While the literature analyzing the effect of monetary policy on stock prices is large,[3] the feedback from stock returns to monetary policy is not robustly understood due to the endogeneity problem between stock returns and interest rates. The objective of this study is to provide evidence that can improve our understanding of the reaction of monetary policy to the stock market using a novel identification strategy.

Any analysis of the Fed's reaction to the stock market has to deal with an identification problem. Stock returns respond to changes in interest rates. Furthermore, stock returns and interest rates are simultaneously affected by macroeconomic news. This makes it difficult to estimate the effect of the stock market on monetary policy. Previous studies attempt to address the simultaneity problem using different approaches. For example, Bjørnland and Leitemo (2009) use a structural vector autoregressive (SVAR) model identified by a combination of restrictions to account for the simultaneity of the interdependence between the stock market and the federal funds rate. They show that a stock price shock leads to an increase in the interest rate in contrast to the findings of other VAR studies that do not account for the simultaneous interdependence (e.g., Lee, 1992).

Rigobon and Sack (2003) use identification through heteroskedasticity to estimate the reaction of monetary policy to the stock market by using shifts in volatility to identify the slope of the policy reaction function. They use daily stock returns and interest rates from 1985 to 1999 and find a statistically significant response of Fed policy to stock returns. However, Furlanetto (2011)

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[3] Examples of studies that investigate the effects of monitory policy on the stock market include Bernanke and Kuttner (2005), Ehrmann and Fratzscher (2004), Wongswan (2009), Kontonikas, MacDonald and Saggu (2013), Gu, Kurov and Wolfe (2018), Cieslak, Morse and Vissing-Jorgensen (2019), and Paul (2020).

shows that Rigobon and Sack's (2003) findings are driven to a large extent by the Fed's reaction to the stock market crash of 1987 and finds no significant response of monetary policy to stock returns during 2003-2007. Aastveit, Furlanetto, and Loria (2017) estimate a recursively identified SVAR model with quarterly data from 1975 to 2008. They find some evidence of time variation in the response of monetary policy to house prices and stock prices. However, similar to Furlanetto (2011), they find a statistically significant response of policy to stock prices only around the stock market crash of 1987. These findings indicate a need for an identification approach that uses high-frequency data to increase precision of estimates and does not assume that the response of monetary policy to stock prices is constant over long periods. Our paper addresses this need.

We make two important contributions to the literature. The first contribution is methodological. We propose an identification approach that uses intraday periodicity in volatility to estimate the response of monetary policy expectations to stock returns. Similar to Rigobon and Sack (2003), our approach is simple and does not suffer from shortcomings of other widely used approaches, such as SVAR models. As argued in Summers (1991), "natural experiments that provide identifying variation in important variables" likely result in better estimates of structural parameters. We achieve a similar aim by using the upward shift in volatility in index futures markets at the time of the stock market opening.

Our approach differs from Rigobon and Sack's (2003) in the following ways. First, our approach identifies the reaction of monetary policy to stock returns under a weaker set of assumptions than required by the identification approach of Rigobon and Sack (2003). For example, we do not assume that the response of monetary policy to the stock market and the effect of policy shocks on stock prices are stable over long periods that may include different macroeconomic environments or different monetary policy regimes. Second, whereas Rigobon and Sack (2003) use daily data and search for volatility regimes within a fifteen-year period, we use intraday futures data and exploit the recurring increase in volatility of index futures returns at the stock market opening. Third, Lütkepohl (2013) highlights that identification through heteroskedasticity methodology similar to the one used by Rigobon and Sack (2003) depends on the volatility regimes being known, which is usually not the case in practice. The uncertainty about the timing of regime changes negatively affects the reliability of inference. Our intraday volatility regimes are known because they are determined by market structure. Furthermore, Rigobon and Sack's (2003) methodology assumes that volatility shifts occur exogenously, even though volatility is closely linked to economic activity and monetary policy.[4] Lütkepohl (2013) also notes that some volatility regimes may be short-lived, leading to potential small sample issues.[5]

The main benefit of our approach is that the intraday volatility shift occurs every trading day at the same time and is caused by the stock market opening rather than by endogenous economic fluctuations. Moreover, because the volatility shift occurs every day, we are able to examine the response of monetary policy to the stock market in different macroeconomic environments. We formally test whether the Fed's response to the stock market is symmetric in recessions and expansions (as defined by the National Bureau of Economic Research) and in bull and bear markets (as defined by Pagan and Sossounov (2003) algorithm). Our approach is much easier to implement in practice than other identification through heteroskedasticity methods and can be applied in various contexts.

Our second contribution is empirical. Bunzel and Enders (2010) document that the Federal Reserve engages in "opportunistic" monetary policy in which the Federal Reserve engages in

[4] See, for example, Schwert (1989), Bekaert and Hoerova (2014), Bekaert, Hoerova, and Lo Duca (2013), and Cremers, Fleckenstein, and Gandhi (2021).

[5] For example, three of the four variance regimes in Rigobon and Sack (2003) taken together account for less than 10% of the sample.

active policy when inflation is high relative to the Fed's target and the output gap is negative. This suggests that Fed policy is likely state dependent. We build upon their work and demonstrate that the response of monetary policy expectations to the stock market is state dependent. Consistent with the existence of the Fed put, this reaction sharply increases during recessions and bear markets. We find that a 10% decline (increase) in the stock market increases the likelihood of a 25-basis-point cut (increase) in the policy rate by about 50% during bear markets. The corresponding increase in the likelihood of policy action during bull markets is only about 14%. In other words, we do not find evidence that the Fed has tried to "lean against the wind" and deflate high valuations in equity markets.[6] This finding is consistent with the literature exploring the asymmetry in the reaction of monetary policy to asset prices. For example, Ravn (2012) uses the methodology of Rigobon and Sack (2003) and shows that the Fed is more likely to ease policy in response to a drop in stock prices but does not respond to a stock price increase, although the results are sensitive to the choice of covariance regimes included in the estimation.

Using a textual analysis framework, Cieslak and Vissing-Jorgensen (2021) document that negative tone about the stock market in the FOMC discussions leads to cuts in the federal fund rate target. Their empirical approach has important advantages, since it involves detailed analysis of monetary policy discussions and links these discussions to policy decisions. However, it relies on FOMC meetings, which normally occur only eight times a year. As mentioned above, we use intraday futures data from every trading day. This allows estimating the response of policy expectations to stock returns with high precision and comparing the estimates for adverse and positive economic environments. We find that the estimates of the policy response coefficient are

[6] In a theoretical study, Pavasuthipaisit (2010) finds that the strategy of leaning against the wind is optimal because asset prices are a useful economic indicator.

statistically significant in all subsets of our 22-year sample period but are significantly larger in recessions and bear markets.

2. Data and Methodology

2.1. Data and Sample Selection

Following Rigobon and Sack (2004), we describe the structural relationship between monetary policy and stock returns using the following equations:

$$\Delta i_t = \beta R_t + \gamma z_t + \varepsilon_t, \quad (1)$$

$$R_t = \alpha \Delta i_t + z_t + \eta_t, \quad (2)$$

where Δi_t is the change in the policy interest rate, R_t is the stock return, and z_t represents common macroeconomic shocks influencing stock prices and interest rates. ε_t and η_t are innovations to the policy rate and stock returns, respectively. Similar to Rigobon and Sack (2003, 2004), we assume that these innovations are uncorrelated with each other and with the common shocks z_t. The coefficient α, which measures the response of stock returns to monetary policy, is the focus of the large previous literature mentioned in the introduction. The main goal of our paper is estimating the coefficient β, which captures the reaction of monetary policy to the stock market. Neither of these two parameters can be consistently estimated with OLS because of the simultaneity of the relation between monetary policy and stock returns and due to the presence of unobserved economic shocks z_t. Panel A in Figure 1 illustrates this simultaneity problem.

[Insert Figure 1 here]

Andersen, Bollerslev, Diebold and Vega (2007) use conditional heteroskedasticity of five-minute futures returns to identify contemporaneous responses of stock, government bond and foreign exchange markets to one another. Monetary policy expectations, reflected in interest rate futures prices, quickly react to new information. For example, these expectations fully adjust to scheduled macroeconomic announcements within one minute after the announcement (Ederington and Lee, 1995). Therefore, we believe that it is reasonable to examine contemporaneous links between intraday interest rate and equity futures prices.

To measure the short-term interest rate, i_t, we use the rate on the nearby Eurodollar futures.[7] This measure of the short-term rate has been used in previous studies. For example, Rigobon and Sack (2004) use daily changes in the rate on the nearby Eurodollar futures contracts in their analysis of the impact of monetary policy on asset prices. Gürkaynak, Sack, and Swanson (2007) show that Eurodollar futures provide good forecasts of the future fed funds rate.[8] The Eurodollar futures contracts are much more liquid than the fed funds futures. They are also less influenced by shifts in the timing of policy decisions that have no effect on the expected near-term path of monetary policy (Rigobon and Sack, 2004). It is important to note that because we use interest rate futures contracts rather than the effective federal funds rate or another interest rate, we are capturing the market's expectation of how monetary policy is likely to respond to the stock market. Beginning with Kuttner (2001), interest rate futures prices have been used extensively as forecasts of monetary policy.[9] Most of the studies looking at the effect of monetary policy on stock prices cited in the introduction use this approach.

To measure stock returns, R_t, we use the E-mini S&P 500 futures, which were introduced in September 1997 and trade on an electronic trading platform, Globex. The Eurodollar and E-

[7] The expiration months of Eurodollar futures contracts are March, June, September and December. The nearby contract becomes relatively illiquid in its last few days of trading. Therefore, we switch to the next-to-mature contract when its daily contract volume exceeds the nearby contract volume.

[8] In a related paper, Gürkaynak, Sack and Swanson (2005) use principal components of intraday changes in fed funds futures and Eurodollar futures prices after policy announcements of the FOMC to estimate unexpected changes in the Fed's current policy rate and in the future path of policy.

[9] Interest rate futures prices also contain risk premia. However, as noted by Piazzesi and Swanson (2008), these risk premia tend to change slowly and are "differenced out" when one uses high frequency changes in futures prices.

mini S&P 500 futures data are obtained from Genesis Financial Technologies and Tick Data. Based on the availability of the E-mini futures data, our sample period begins in October 1997. The endpoint of the sample period is December 2019. Globex operates virtually around the clock, and trading is quite active after 8 a.m. ET. However, the level of trading activity and volatility in the E-mini S&P 500 futures sharply increases after the opening of the stock market and the beginning of open outcry trading in the regular S&P 500 futures at 9:30 a.m. We use this predictable increase in volatility caused by market structure as our identification tool.

2.2. Identification through Intraday Shift in Volatility

Rigobon and Sack (2003) propose using heteroskedasticity of the daily aggregate stock returns to estimate the response of monetary policy to the stock market. Panel B of Figure 1 illustrates the intuition for this identification approach. Suppose we could find a period with higher variance of the stock return innovations. If the variances of the monetary policy shocks ε_t and economic shocks z_t remained unchanged, the values of stock returns and interest rate changes would align more closely with the monetary policy reaction to stock returns. This provides the basis for the identification of the parameter of interest (β).

Using a sample period from 1985 to 1999, Rigobon and Sack (2003) show that the Fed is expected to increase (cut) the policy rate by about 25 basis points in response to a 10 percent increase (decline) in the S&P 500 index. This identification approach relies on regime shifts in the covariance of the structural shocks. The covariance regimes are identified by computing the covariance matrix of reduced-form shocks to stock returns and interest rates in a 30-day rolling window. However, as noted by Lütkepohl (2013), the parameter estimates depend on correctly identifying the volatility regimes. In a related study, Rigobon and Sack (2004) show that the response of stock returns to monetary policy can be identified using the increase in variance of policy shocks on days of important policy announcements. We propose a conceptually similar identification through heteroskedasticity approach to measure the effect of stock returns on monetary policy. Instead of estimating the volatility regimes following Rigobon and Sack (2003), we use the intraday periodicity in volatility observed in index futures markets.

Our estimation approach relies on using index futures returns and Eurodollar futures rate changes computed over 15-minute intervals.[10] For the first few years of our sample period (until February 20, 2003) we have Eurodollar futures data only for the floor trading hours from 8:20 a.m. to 3:00 p.m. ET.[11] After February 20, 2003, the available Eurodollar futures data is for the same trading hours as the trading hours of the E-mini S&P 500 futures, with both markets open for trading essentially around the clock, with a break from 5:00 p.m. to 6:00 p.m. ET. The index futures returns and Eurodollar futures rate changes show evidence of a small amount of negative autocorrelation, perhaps due to price discreteness and bid-ask bounce. To remove this autocorrelation and possible lead-lag relation between the two variables, in the analysis that follows we use residuals from a vector autoregressive (VAR) model of 15-minute E-mini S&P 500 futures returns and Eurodollar futures rate changes. The model includes two lags of the two variables.[12] The lag length is selected using the Schwarz information criterion. We use all available intraday data during the sample period to estimate the VAR model.

Panel A1 in Figure 2 shows variances of the VAR residuals with the E-mini S&P futures' variance denoted by the dashed line and the Eurodollar rate variance denoted by the solid line. The figure shows that the variance of the E-mini S&P index futures returns in the interval from 9:30

[10] As a robustness check, we also used 30-minute intervals. The results were very similar.
[11] Therefore, before February 2003 the first Eurodollar futures rate change for each day is computed from 8:20 a.m. to 8:30 a.m. ET.
[12] The results are essentially unchanged if we use raw E-mini S&P 500 futures returns and Eurodollar futures rate changes in the estimation described below.

a.m. to 9:45 a.m. increases by approximately a factor of five compared to the previous 15-minute interval, whereas the variance of the Eurodollar futures rate shows only a slight increase over the same 15-minute interval. The shift in variance of index futures returns is driven by the increase in trading activity and the resulting revelation of information in the stock market after the market opening. The spike in the Eurodollar variance rate at 2:30 p.m. is due to FOMC announcements. For comparison, Panel A2 of Figure 2 displays the Eurodollar variance and the E-mini S&P futures' variance on non-FOMC announcement days; as expected, the spike in the Eurodollar variance at 2:30 p.m. is no longer present.

Panel B1 in Figure 2 shows that the correlation and the covariance of E-mini S&P index futures returns and Eurodollar futures rate changes in the interval from 9:30 a.m. to 9:45 a.m. increases significantly from the previous 15-minute interval. This increase in correlation is driven by the increase in the relative volatility of stock return innovations. It is consistent with endogenous response of monetary policy expectations to stock returns. The shift in covariance of stock returns with interest rate changes can be used to estimate the parameter β in equation (1). The only intraday interval, except the interval that ends at 8:30 a.m., in which this covariance becomes negative is the interval from 2:00 p.m. to 2:30 p.m. containing scheduled FOMC announcements, which is consistent with the increase in variance of monetary policy shocks after FOMC announcements shown in Panel A1 of Figure 2. As above, Panel B2 displays the correlation and covariance on days without FOMC announcements and, as expected, the negative covariance is no longer present during the afternoon.

[Insert Figure 2 here]

Panel A in Figure 3 shows that the trading activity in the E-mini S&P 500 futures increases by approximately a factor of seven in the 15-minute interval ending at 9:45 a.m. compared to the previous 15-minute interval. Does this trading activity contain information and, therefore, lead to permanent price changes? One could argue that the increase in intraday volatility in the E-mini S&P 500 futures after the market opening at 9:30 a.m. may be driven by noise trading rather than by information. French and Roll (1986) provide evidence that the increase in variance of stock returns during exchange trading hours is driven primarily by private information, which is incorporated in prices through trading. Holden and Subrahmanyam (1992) show theoretically that trading on private information generated during non-trading hours is concentrated at the market opening. Prior studies provide evidence that investor order flow aggregates private information and transmits it into asset prices. For example, Evans and Lyons (2002) show that order flow in the foreign exchange market is a key determinant of foreign exchange rates. Similarly, Menkveld, Sarkar, and van der Wel (2012) show that order flow in the U.S. Treasury futures market affects Treasury yields. Kurov (2008) provides similar evidence for U.S. index futures markets.

[Insert Figure 3 here]

To test whether price changes in the E-mini S&P 500 futures market at the time of the stock market opening are informative, we examine the relative magnitude of price discovery by intraday interval using weighted price contribution (WPC), defined as:

$$WPC_i = \sum_{t=1}^{T} \left(\frac{|R_t|}{\sum_{t=1}^{T} |R_t|} \right) \frac{R_{i,t}}{R_t}, \tag{3}$$

where $R_{i,t}$ is the return in the intraday interval i on day t and R_t is the total close-to-close return for day t. The term in parentheses is the weighting factor for each day. The term outside of the parentheses is the relative contribution of interval i on day t to the total return on day t. The WPC sums up to one by construction. The WPC is proposed by Barclay and Warner (1993) and is commonly used to estimate contributions of different trade sizes, trading venues or intraday time intervals to price discovery.[13] In our case, the WPC represents the percentage of the daily cumulative price change that can be attributed to the given 15-minute intraday interval.

Panel B of Figure 3 displays the informational contributions of different intraday intervals in the E-mini S&P 500 futures market. The WPC follows roughly the same intraday U-shape pattern as the trading volume and volatility in the E-mini S&P 500 futures market. The interval from 9:30 a.m. to 9:45 a.m. makes a much larger contribution to the daily returns than does the immediately preceding 15-minute interval. The WPC of the 15-minute interval ending at 9:45 a.m. is about 4.6%, suggesting that this interval makes a substantial contribution to the daily cumulative price change. We conclude that price changes in the E-mini S&P 500 market at the time of the stock market opening are informative and are not primarily driven by noise trading.

If the variance of economic news shocks σ_z was substantially higher in the 15-interval ending at 9:45 a.m. than in the previous 15-minute interval, we would observe a substantial increase in the variance of Eurodollar futures rate changes, and we do not find such variance increase in the data. Based on the preceding discussion, it is reasonable to assume that after 9:30 a.m. the variance of stock return shocks (σ_η) increases, and the variances of interest rate shocks (σ_ε) and economic news shocks (σ_z) remain constant.[14] To obtain an estimator of the response of monetary policy to stock returns, equations (1) and (2) are written in reduced form as follows:

$$\Delta i_t = \frac{1}{1-\alpha\beta}[(\beta+\gamma)z_t + \beta\eta_t + \varepsilon_t],$$

$$R_t = \frac{1}{1-\alpha\beta}[(1+\alpha\gamma)z_t + \eta_t + \alpha\varepsilon_t].$$

[13] See, for example, Huang (2002) and Cheng, Jiang and Ng (2004).
[14] Most major scheduled U.S. macroeconomic announcements are made at 8:30 a.m. and 10:00 a.m. As Figure 2 shows, volatility of returns and rate changes is relatively high in the intervals that contain these announcements. The only scheduled macroeconomic announcement made between 9:15 a.m. and 9:45 a.m. is the industrial production and capacity utilization announcement made by the Federal Reserve Board at 9:15 a.m. in the middle of each month. Dropping days of these announcements from the sample has little effect on the results.

As argued above, the intraday interval from 9:30 a.m. to 9:45 a.m. (interval 1) has higher variance of the stock return shocks η_t than the immediately preceding 15-minute interval (interval 2). All other model parameters are assumed to be equal in both intervals. Under these assumptions, the covariance matrices of stock returns and interest rate changes for the two intervals are:

$$\boldsymbol{\Omega_1} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \sigma_\varepsilon + \beta^2\sigma_{\eta 1} + (\beta+\gamma)^2\sigma_z & \alpha\sigma_\varepsilon + \beta\sigma_{\eta 1} + (\beta+\gamma)(1+\alpha\gamma)\sigma_z \\ . & \alpha^2\sigma_\varepsilon + \sigma_{\eta 1} + (1+\alpha\gamma)^2\sigma_z \end{bmatrix},$$

$$\boldsymbol{\Omega_2} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \sigma_\varepsilon + \beta^2\sigma_{\eta 2} + (\beta+\gamma)^2\sigma_z & \alpha\sigma_\varepsilon + \beta\sigma_{\eta 2} + (\beta+\gamma)(1+\alpha\gamma)\sigma_z \\ . & \alpha^2\sigma_\varepsilon + \sigma_{\eta 2} + (1+\alpha\gamma)^2\sigma_z \end{bmatrix}.$$

The difference between these covariance matrices is:

$$\Delta\boldsymbol{\Omega} = \boldsymbol{\Omega_1} - \boldsymbol{\Omega_2} = \frac{(\sigma_{\eta 1}-\sigma_{\eta 2})}{(1-\alpha\beta)^2}\begin{bmatrix} \beta^2 & \beta \\ \beta & 1 \end{bmatrix}. \tag{4}$$

The first term in equation (4) can be treated as a single parameter $\lambda \equiv \frac{(\sigma_{\eta 1}-\sigma_{\eta 2})}{(1-\alpha\beta)^2}$. $\sigma_{\eta 1}$ and $\sigma_{\eta 2}$ are variances of stock return innovations in the two intervals. Therefore, λ captures the degree of heteroskedasticity of stock return innovations between the two intervals. The two parameters (λ and β) can be estimated using the generalized method of moments (GMM). Since we have three moment conditions to estimate these two unknown parameters, the GMM estimator is overidentified. The GMM estimation uses data only from the two 15-minute intervals around the stock market opening at 9:30 a.m.

The GMM estimator is based on a set of moment conditions:

$$E(b_t) = 0,$$

where $b_t = vech(y_t y_t' - \lambda[\beta\ 1]'[\beta\ 1])$ and $y_t = [\Delta i_t\ R_t]$. According to the covariance matrix equations above, we have three moment conditions: the changes in variances of index futures returns and Eurodollar futures rate changes and the change in their covariance. To estimate the two parameters (λ and β), the GMM estimator minimizes the sample average of b_t. Therefore, the GMM estimator is

$$\{\hat{\beta}, \hat{\lambda}\} = \operatorname{argmin} \left[\sum_{t=1}^{N} b_t\right]' S_N^{-1} \left[\sum_{t=1}^{N} b_t\right],$$

where the weighting matrix S_N^{-1} is computed as the inverse of the covariance matrix of the moment conditions. As mentioned above, in our case the GMM estimator is overidentified. The overidentifying restrictions can be tested using the following statistic proposed by Hansen (1982):

$$J = N \left[\sum_{t=1}^{N} b_t\right]' S_N^{-1} \left[\sum_{t=1}^{N} b_t\right].$$

Under the null hypothesis, this statistic is asymptotically chi-square distributed with the number of degrees of freedom equal to the number of overidentifying restrictions. Since we use three moment conditions to estimate the two parameters, we have one overidentifying restriction. If the null hypothesis of this test is rejected, it means that either some of our identification assumptions are invalid or the model is misspecified.

2.2.1. Comparison with Rigobon and Sack's (2003) Identification Approach

As noted in Summers (1991) and Rigobon and Sack (2003), many SVARs suffer from orthogonalization problems in that the identification assumptions used in the covariance matrix of residuals are not tenable.[15] Using high-frequency data as in Cochrane and Piazzesi's (2002) and D'Amico and Farka's (2011) circumvents some of the orthogonalization assumptions needed to identify the structural parameters in SVARs. Often one can use high-frequency methods to identify the shock of interest and then aggregate the shocks in longer time intervals. For example, D'Amico

[15] For example, in a monthly bivariate SVAR of interest rate changes and stock returns, in order to identify α and β in equations (1) and (2), a Choleski decomposition with interest rates ordered first would assume that interest rates do not respond within the month to changes in stock returns, which is certainly not plausible.

and Farka (2011) and Gertler and Karadi (2015) aggregate high-frequency financial and monetary shocks into a monthly time series which allows them to model the dynamic effects of the monetary shocks on broader macroeconomic aggregates (i.e., the price level, output and unemployment) and at a monthly frequency. We contribute to this literature by identifying the structural parameters using high-frequency data in conjunction with heteroskedasticity that results from market microstructure.

It is useful to compare our estimator of the response of monetary policy to stock returns with the identification through heteroskedasticity estimator of β proposed by Rigobon and Sack (2003). They divide the sample of daily stock returns and interest rate changes into four regimes based on variances and covariances of reduced-form shocks and use these regimes for identification. Elevated stock return volatility is the key criterion used to define the covariance regimes. The parameters α, β, γ and σ_ε are assumed to be constant across the regimes. However, each of these parameters is likely to change in bear markets, when stocks become more volatile.[16] This makes the identification assumptions problematic. Hence, it is reasonable to estimate the model for bull and bear market periods separately. We estimate the model separately for different periods and compare the results.[17]

Our identification approach has several advantages. First, instead of searching for covariance regimes across days, we use predictable variation in volatility within each day. This makes the identification assumptions mentioned above more plausible. Second, we can also assume that the variance of common shocks, σ_z, is constant between the first and second half of

[16] For example, Chen (2007) shows that the effect of monetary policy on stock returns (α) is much larger in absolute value in bear markets then in bull markets. Basistha and Kurov (2008) find that the response of the stock market to monetary policy news is much stronger in recessions and in tight credit conditions.
[17] Andersen, Bollerslev, Diebold and Vega (2007) also estimate their model separately in expansion and recession subsamples in their analysis of contemporaneous links among global stock, bond and foreign exchange markets.

the 30-minute interval used in estimation. With fewer parameters to estimate due to this assumption, our identification approach requires only one shift in the covariance matrix, as opposed to at least three regimes required to implement the Rigobon and Sack (2003) procedure. Our identification assumptions can be tested using a standard test of overidentifying restrictions. Finally, our identification approach allows estimating the time-varying response of monetary policy to stock returns. In comparison, the Rigobon and Sack (2003) approach requires at least several years of data to estimate β, making it difficult to analyze time variation in the response of monetary policy to the stock market.

3. Results

3.1. Full Sample

Table 1 displays the full sample results obtained from the methodology outlined in Section 2.2. The policy response (β) for the entire sample is 0.0068 and statistically significant at the 1% level. Based on this estimate, a 10 percent move in the S&P 500 index moves the expected short-term interest rate by about 6.8 basis points in the same direction. In terms of the Fed's expected response, a 10 percent decline in the stock market increases the likelihood of a 25-basis-point cut in the policy rate by about a quarter ($6.8/25 = 0.27$).

[Insert Table 1 here]

3.2. Expansions vs. Recessions

One benefit of using the methodology outlined in Section 2.2 is that it enables one to test whether the structural response of the Federal Reserve to the stock market depends on the state of the economy. That is, we are positing a different structural response during expansions versus recessions. We decompose our sample into expansionary and recessionary periods based on the

NBER business cycle dates. We believe that the NBER recession dates provide a reasonable way to divide the sample given that the financial crisis roughly corresponds to the NBER recession dates from January 2008 to June 2009. The NBER recession dates also provide a reasonable date on which the Federal Reserve began to use unconventional policy tools. Therefore, we are able to examine the effect of the stock market on monetary policy during a recession (April 2001 – November 2001) and two expansions (October 1997 – March 2001 and December 2001 – December 2007) under conventional monetary policy, as well as a recession (January 2008 – June 2009) and an expansion (July 2009 – December 2019) during unconventional policy.

The GMM estimators of β and α for good and bad times reported in Tables 2 through 4 are asymptotically normally distributed with the same mean under the null and variance σ_1 and σ_2, respectively, and covariance σ_{12}. Then, the difference between the two estimates shown in Tables 2 through 4 under the null is mean zero with variance $\sigma_1 + \sigma_2 - 2\sigma_{12}$. However, since returns in different periods are independent, the covariance σ_{12} must be zero. Therefore, we compute the standard error of the coefficient difference as the square root of the sum of squared standard errors of the two estimates. The resulting test statistic is asymptotically normal, and we use the usual standard normal critical values. Using Student's *t* critical values does not change the statistical significance of the coefficient differences.

According to the Fed put hypothesis, the response of monetary policy to stock returns should be stronger in recessions than in good economic times. Panel A of Table 2 shows the GMM estimates of the λ and β parameters during recessions and expansions. First, note that the estimate of β during recessions is 0.0108 versus 0.0053 during expansions and both are statistically significant at the 1% level; the policy response of the Fed is roughly twice as high during recessions relative to expansions. The difference between the estimated responses of monetary policy to stock returns in expansions and recessions is statistically significant at the 1% level. Also, observe that for both expansions and recessions the test of overidentifying restrictions suggests that our identifying assumptions are not rejected.

[Insert Table 2 here]

It is possible that the low estimate of the reaction of policy expectations to the stock market during the most recent economic expansion is due, at least in part, to the short-term interest rates being constrained by the zero lower bound. To address this concern, we repeat our analysis while excluding the zero lower bound period from December 16, 2008 to December 16, 2015. Panel B of Table 2 reports the results that are similar to the results in Panel A. The estimate of β during recessions is now 0.0133 versus 0.0077 during expansions and the difference between the two estimates is statistically significant at the 5% level.

Panel C of Table 2 displays the parameter estimates for the expansions and recession as given by the NBER dates under *conventional* monetary policy whereas Panel D displays the results under *unconventional* monetary policy. The first column in each panel displays the results from recessions and the second column displays the results from expansions. Note that we have two recessions in our sample period. The first recession spanned from April 2001 to November 2001 and was relatively mild; the unemployment rate only increased from 4.3% at the beginning of the recession to 5.5% at the end. In contrast, during the second recession (January 2008 – June 2009) the unemployment rate increased from 5% at the beginning of the recession to 9.5% at the end. Interestingly, the responses of policy to the stock market in both recessions are approximately the same. In Panel C, β is 0.0116 in the 2001 recession and in Panel D during the more recent recession, β is 0.0107. Both estimates are significant at the 1% level; however, the degree of heteroskedasticity of stock return innovations is much greater during the 2008-2009 recession than in the 2001 recession as indicated by the estimates of λ.

Based on the β estimate for the 2001 recession in Panel C, a 10 percent move in the S&P 500 index moves the expected short-term interest rate by about 11.6 basis points in the same direction. This means that, for example, a 10 percent fall in stock prices increases the likelihood of a 25-basis-point cut in the policy rate by about half $(11.6/25 = 0.46)$. The estimates of β during the two expansionary parts of the sample are dramatically different from each other. The estimate during the expansions from 1997 to 2001 and from 2001 to 2007 is 0.0081. This estimate is significant at the 1% level and similar to the estimate obtained by Furlanetto (2011) for the 1988-2003 period. However, during the expansion that started in 2009, the estimate of β falls to 0.0025 and is also statistically significant at the 1% level. Given our measure of monetary policy changes, this could be a result of short-term interest rates being at the zero lower bound over the 2009-2015 period.

The third column in each panel shows the difference between the coefficients during recessions and expansions. Note that the difference between the coefficients is statistically significant at the 1% level for the unconventional monetary policy period in Panel D but not for the conventional policy period in Panel C. The difference between the recession and expansion estimates is more than twice as large during the unconventional monetary policy period. In terms of the market expectations of policy actions, the results are dramatically different between the expansions. Our results suggest that a 10 percent increase in the stock market during an expansion prior to 2008 increases the likelihood of a 25-basis-point increase in the expected policy rate by about one-third. During the most recent expansion, this likelihood falls to about ten percent.

3.3. Bull vs. Bear Markets

We use the algorithm proposed by Pagan and Sossounov (2003) to identify turning points of bull and bear market phases to examine if the Fed responds to the stock market symmetrically in bull and bear markets. The algorithm proposed by Lunde and Timmermann (2004) produces the same market cycle turning points in our sample period. We use the turning points based on these algorithms reported in Maheu, McCurdy and Song (2012). While there is significant overlap between recessions and bear markets, the dates do differ. The 2001 recession began in April 2001 whereas the bear market began a year earlier in April of 2000; the recession ended in November of 2001, but the bear market did not end until October of 2002 according to the Pagan and Sossounov methodology. During the Great Recession, the turning points for the economy and the stock market are much closer. The recession began in January 2008 and the bear market began in November 2007, whereas the bear market ended in March 2009 and the recession ended in June 2009.

Panel A of Table 3 displays the results from all bull markets and all bear markets in our sample period and Panel B displays the results by excluding the zero lower bound period. In addition, Panel C displays the results during conventional monetary policy and Panel D shows the results during unconventional monetary policy. The results in Panel A show that the response of monetary policy to the stock market approximately triples in bear markets compared to bull markets. The estimated coefficients in Table 3 are largely similar to those in Table 2. During recessions, the estimated responses of policy in Table 2 are 0.0108, 0.0133, 0.0116, and 0.0107 in the combined, excluding zero lower bound period, conventional policy and unconventional policy samples, respectively. During bear markets, the corresponding estimates in Table 3 are 0.0114, 0.0126, 0.0116, and 0.0114. As shown in the last column of Table 3, the hypothesis that the policy response coefficients in bull and bear markets are equal is rejected at the 1% level in all four cases. In terms of the likelihood of Federal Reserve action, note that the probabilities in bear markets are very similar to those in recessions; a 10 percent decline in the stock market increases the likelihood of a 25-basis-point cut in the Federal Funds rate by almost 50 percent. In bull markets, a 10 percent increase in the stock market during conventional monetary policy increases the likelihood of a 25-basis-point rate hike by about 20 percent whereas the corresponding likelihood during unconventional policy is around ten percent ($2.5/25 = 0.10$).

[Insert Table 3 here]

It is noteworthy that the difference in the policy response between recession and expansion under conventional monetary policy is not statistically significant, as shown in Panel C of Table 2. However, the difference in the policy response between bear and bull markets during the same conventional policy period is significant. A possible explanation is that the bear market of 2000-2002 was much longer than the recession of 2001. As a robustness check, we use an alternative approach to identify turning points of bull and bear market phases. Specifically, following Chen (2007), we estimate the probabilities of bull and bear markets using a Markov-switching model of stock returns that allows the mean and the variance of returns to vary between two regimes. We use weekly S&P 500 returns and estimate the probabilities of these regimes: a regime with a higher mean and lower variance of returns (bull market) and a regime with a lower mean and higher variance (bear market). Following Chen (2007) and Kurov (2010), we define bear markets as the periods when the smoothed probability of the bear market regime is above 0.5. We then estimate the response of monetary policy to the stock market separately in bull and bear market periods. The results, available upon request, are very similar to those in Table 3.

Our sample period includes the zero lower bound period, which might result in Eurodollar futures being a poor measure of the monetary policy expectation. As a robustness check, we use the implied yields of the two-year Treasury note futures contracts as a reasonable proxy for changes in monetary policy expectations during the period of unconventional monetary policy (e.g., Hanson and Stein, 2015). The results are qualitatively similar to the results reported in Tables 2 and 3. The GMM parameter estimates for this test are available upon request.

Overall, our results are not consistent with the Fed "leaning against the wind" by trying to deflate stock market bubbles.[18] The differences in the magnitude of the policy response coefficients between adverse and positive economic environments documented in this and the previous sub-section suggest the existence of the Fed put. Our results strongly support Roubini's (2006) characterization that the Federal Reserve has followed a "mop up after" approach to monetary policy and asset prices. That is, our results are consistent with an asymmetric response of policy to large increases and decreases in asset prices: no tightening of policy on the way up but aggressive monetary easing on the way down to contain the collateral damage to other parts of the economy. Our findings are also broadly consistent with Cieslak and Vissing-Jorgensen (2021) who use textual analysis of FOMC minutes and transcripts and show that negative intermeeting stock returns predict subsequent policy easing.

3.4. Analysis of intraday returns and rate changes on FOMC announcement days

We have established that the feedback from stock returns to monetary policy is stronger in recessions and bear markets than in good economic times and bull markets. It is interesting to examine if these results hold on days of scheduled FOMC meetings when the Federal Reserve announces its decisions about monetary policy. Moreover, the increased variation around FOMC

[18] Bernanke (2002) argues that it is very difficult for a central bank to effectively act against asset bubbles.

announcements, and particularly the higher variance of monetary policy shocks around these events, gives us another volatility regime. This enables us to jointly estimate the response of monetary policy expectations to stock returns and the response of the stock market to monetary policy news on FOMC announcement days. We focus on announcements following scheduled FOMC meetings because we want to test how policy expectations respond to stock returns shortly before a policy decision when the market knows that a policy decision will be made and released later that day. There are 178 such announcements during our sample period. Panel A1 of Figure 2 shows a large increase in the variance of the Eurodollar futures rates at times of scheduled FOMC announcements despite the fact that such announcements generally occur only eight times a year whereas the figure uses data for all trading days.

Figure 4 shows intraday variation in volatility and comovement of index futures returns and Eurodollar futures rate changes on days of scheduled FOMC meetings. To maintain consistency with our previous empirical tests, we use the residuals from a VAR model that includes two lags of the Eurodollar futures rate changes and the E-mini S&P 500 futures returns. The scheduled FOMC announcement time was 2:15 p.m. from September 1994 to March 2011. Between April 2011 and January 2013, about half of the announcements were made at 12:30 p.m., and the rest were released at 2:15 p.m. Since March 2013, FOMC statements after all scheduled meetings have been released at 2:00 p.m. Overall, for about 95% of the FOMC announcements in our sample the scheduled announcement time was 2:15 p.m. or 2:00 p.m. Panel A of the figure shows that the variance of the Eurodollar futures rate changes increases by a factor of more than 50 between 1:45 p.m. and 2:30 p.m. Panel B of Figure 4 shows that the covariance between the Eurodollar futures rates changes and the E-mini S&P 500 futures returns turns sharply negative in the same time interval. These changes in the covariance matrix of stock returns and rate changes can be used to identify the response of stock prices to monetary policy.

[Insert Figure 4 here]

As stated in equation (4), the difference between the covariance matrices of Eurodollar futures rate changes and the E-mini S&P 500 futures returns in the 15-minute intervals ending at 9:30 a.m. and 9:45 a.m. is:

$$\Delta^{open}\boldsymbol{\Omega} = \frac{(\sigma_{\eta 1} - \sigma_{\eta 2})}{(1-\alpha\beta)^2}\begin{bmatrix}\beta^2 & \beta \\ \beta & 1\end{bmatrix} = \frac{\Delta_\eta^{open}}{(1-\alpha\beta)^2}\begin{bmatrix}\beta^2 & \beta \\ \beta & 1\end{bmatrix}, \tag{5}$$

where Δ_η^{open} is the change in the variance of index futures return innovations after the stock market opening. In addition to estimating β, we want to estimate the response of the stock market to monetary policy shocks α. Therefore, we no longer treat the first term in equation (4) as a single parameter. Gürkaynak, Sack and Swanson (2005) show that a 30-minute window around FOMC announcements captures both monetary policy surprises and asset market responses well. Therefore, to take advantage of the change in the covariance matrix around FOMC announcements, we use a 30-minute event window from 15 minutes before to 15 minutes after the scheduled FOMC announcement time.[19] For the pre-announcement window, we use the interval from 45 minutes before to 15 minutes before the scheduled announcement time. To compute index futures returns and rate changes in these 30-minute windows, we sum up the VAR residuals of these variables in the corresponding two 15-minute intervals.

We assume that α, β, and the variance of the common shocks z_t remain stable immediately before and after the FOMC announcements. The difference between the covariance matrices of

[19] Using information from Bloomberg and Dow Jones, Fleming and Piazzesi (2005) show that scheduled FOMC announcements were often released a few minutes before the regular 2:15 p.m. announcement time during the period from 1994 to 2004. We use the event window from 15 minutes before to 15 minutes after the scheduled announcement time to capture all such events while using returns computed on a 15-minute time grid.

Eurodollar futures rate changes and the E-mini S&P 500 futures returns in the two 30-minute intervals is:

$$\Delta^{FOMC}\boldsymbol{\Omega} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \Delta_\varepsilon^{FOMC} + \beta^2\Delta_\eta^{FOMC} & \alpha\Delta_\varepsilon^{FOMC} + \beta\Delta_\eta^{FOMC} \\ . & \alpha^2\Delta_\varepsilon^{FOMC} + \Delta_\eta^{FOMC} \end{bmatrix} \quad (6)$$

Equation (6) contains two new parameters: the changes in variance of monetary policy shocks and stock return innovations around the FOMC announcement, $\Delta_\varepsilon^{FOMC}$ and Δ_η^{FOMC}, respectively. In their estimation of the response of asset prices to monetary policy, Rigobon and Sack (2004) use daily data for days of FOMC announcements and of the Fed Chair's semi-annual testimony to Congress, taking advantage of the increase in variance of monetary policy shocks on these policy days relative to the previous day. They assume that all model parameters except the variance of the monetary policy shocks are equal on policy days and on the previous days. These assumptions are necessary if information available for identification is limited to three moment equations provided by a single covariance matrix shift around monetary policy decisions. In contrast, with the additional covariance matrix shift at the time of the stock market opening we are able to lift one of these assumptions, allowing for a change in the variance of the stock return innovations around the FOMC announcements.

If we assumed that the variance of the stock return innovations remains stable around the announcement, it would mean that all of the approximately 15-fold increase in the variance of the E-mini S&P 500 futures returns around FOMC announcements shown in Panel A of Figure 4 is due to the response of stock returns to monetary shocks. When we make that assumption, which effectively sets Δ_η^{FOMC} equal to zero, the test of overidentifying restrictions is significant at the 1% level in expansions and bull markets and at 10% and 5% levels in recessions and bear markets, respectively, indicating that this assumption is rejected by the data. Moreover, the estimates of the stock market response to policy shocks (α) become implausibly large in absolute value, indicating that imposing the restriction $\Delta_{\eta}^{FOMC} = 0$ severely biases the GMM estimator of α.[20] This strongly suggests that it is useful to take advantage of the two intraday volatility shifts on FOMC announcement days, estimate the two response coefficients (α and β) jointly, and remove one of the identification restrictions imposed in Rigobon and Sack (2004).

The two covariance matrix shifts in equations (5) and (6) provide six moment equations with five unknown parameters (two coefficients and three variance changes). Therefore, the model is overidentified. We estimate the five parameters jointly using GMM. The results are presented in Panels A and B of Table 4. The estimates of β on FOMC announcement days in recessions and bear markets are similar to the corresponding estimates in Tables 2 and 3. However, similar to Gilchrist and Zakrajšek (2013), our estimates are based on small sample sizes due to the focus on FOMC announcement days.

[Insert Table 4 here]

The estimates of the response of monetary policy expectations to stock returns on days of FOMC announcements during economic expansions and bull markets are close to zero and statistically insignificant. This suggests investors believe that the Fed is unlikely to react to recent stock returns in good economic times and during bull markets. Cieslak and Vissing-Jorgensen (2021) note that a key question is the extent to which the Federal Reserve views the stock market as a predictor of future macroeconomic activity or a driver of future economic activity. Obviously, these alternative views are not mutually exclusive and the Fed's interpretation of the informational content within financial markets could be state dependent. However, Cieslak and Vissing-Jorgensen (2021) argue through textual analysis of the FOMC minutes that the driver view is articulated more frequently by FOMC participants.

[20] For example, the resulting GMM estimate of α in bull markets is about –50.

We believe that the similarity of our results in recessions and bear markets on FOMC announcement dates with those in Tables 1 and 2 is consistent with Cieslak and Vissing-Jorgensen (2021) arguments. That is, the Fed responds to declines in equity markets due to concerns that consumption and investment may fall due to wealth effects resulting from the decline in the stock market. At the same time, the estimates of β for expansions and bull markets on FOMC announcement days in Table 4 are substantially different from the corresponding estimates for all trading days in Tables 1 and 2. One possible explanation for this difference is that markets may believe that the Fed may view fluctuations in equity prices as predictors rather than drivers of economic activity during good times. To test this hypothesis, we obtained the Cieslak and Vissing-Jorgensen (2021) data classifying the stock market mentions in the FOMC minutes.[21] The data spans the period from January 1994 to December 2016. Cieslak and Vissing-Jorgensen (2021) classify stock market mentions in the FOMC minutes into six categories: predictor of future economic conditions, driver of economic activity, descriptive, determinants of stock valuation, other, and financial stability.

We calculate the ratio of the number of times that the stock market is mentioned as a driver of economic activity to the total number of mentions of the stock market. Given that the ratio is bounded between zero and one, we used the driver ratio as the dependent variable in a Tobit model and regressed it on a bear market dummy variable (i.e., one in a bear market and 0 otherwise). The coefficient estimate of the bear market dummy is about 0.20 and statistically significant at the 1% level.[22] This result is supportive of the hypothesis that the Fed may view fluctuations in equity prices as a driver rather than predictor of macroeconomic activity during adverse macroeconomic environments.

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[21] We would like to thank Anna Cieslak for providing the data to us.

[22] The Tobit regression estimates are not tabulated for brevity and are available upon request.

As mentioned in Section 2.2, the identification approach of Rigobon and Sack (2003) relies on the assumption that both the reaction of monetary policy to stock returns β and the response of stock returns to monetary policy α are stable over time. Our identification approach does not require these assumptions. Furthermore, we have provided evidence that, consistent with the notion of the Fed put, β increases in bad economic times and in bear markets. It is interesting to test if the response of the stock market to monetary policy shocks, (α), is stable in different states of the economy and market regimes. All of the estimates of the response of stock returns to policy shocks reported in Table 4 are statistically significant. These estimates are similar in magnitude to those reported in previous studies (e.g., Bernanke and Kuttner, 2005; Rigobon and Sack, 2004). For example, our estimate of the stock market response coefficient in expansions and bull markets is about –7.4. Based on this estimate, a hypothetical 25-basis-point unexpected increase in the short-term interest rate leads to an approximately 1.85% decline in the stock market on average. However, it is interesting that the estimates of α are not statistically different in good and bad economic times and in different stock market regimes.[23]

Finally, it should be noted that the statistic for the test of overidentifying restrictions is not significant in any of the four estimations in Table 4, suggesting that our identification assumptions are consistent with the data. It is also noteworthy that the parameter Δ_{η}^{FOMC} that captures the change in the variance of stock return innovations after FOMC announcements is positive and statistically significant in all four estimations in Table 4. Volatility is generated by information flow. Birru and Figlewski (2010) use expectations of stock returns extracted from S&P 500 index options to

[23] The estimated responses of the stock market to monetary shocks in good and bad economic times and market regimes are very similar if we regress the index futures return in the 30-minute event window centered on the scheduled FOMC announcement time on the Eurodollar futures rate change in the same intraday window. If we use Rigobon and Sack's (2004) identification through heteroskedasticity with daily data and the same set of 178 scheduled FOMC announcements as the one analyzed in this section, the GMM estimate of α is about -2.8 and is statistically insignificant. These estimates are not tabulated to save space but are available upon request.

examine how the stock market searches for new equilibrium prices after FOMC announcements. They argue that the market reaction itself produces additional information. As investors trade on this information, they generate further price fluctuations. This iterative process of price discovery that contains a feedback loop generating new information may explain the increase in volatility of the stock market return innovations after FOMC announcements.

Overall, we provide evidence that the response of expectations of future Fed policy to the stock market depends on the state of the economy. That is, in periods of heightened macroeconomic uncertainty, the Fed is much more likely to concern itself with the potential negative wealth effects of asset prices on the real economy. Somewhat surprisingly, we do not find that the response of the stock market to the Fed is state dependent. One caveat to this result is that we omit unscheduled FOMC announcements that are much more likely to take place during recessions and in periods of financial market stress. The stock market's response to monetary policy may still be state dependent but we may not be capturing this effect due to the timing of unscheduled FOMC announcements during periods of crises.

4. Summary and Conclusions

Simultaneity in the relationship between stock returns and interest rates has been a major barrier for examining the feedback from stock returns to monetary policy. We estimate the reaction of monetary policy to stock price movements using a novel identification approach based on the intraday volatility pattern in index futures markets. One of the important advantages of our approach is that it does not rely on the assumption used by Rigobon and Sack (2003) that the model parameters, including the reaction of policy to the stock market, are equal on days of high and low stock return volatility. Consequently, our identification approach allows analyzing time variation in the response of monetary policy to the stock market.

We find that U.S. monetary policy is more responsive to stock returns in recessions and bear markets. This finding is consistent with the existence of the Fed put and a "mop up after" approach of monetary policy to changes in asset prices. That is, the market expects an asymmetric response of monetary policy to changes in asset prices in good and bad economic times. In addition, we jointly estimate the response of stock returns to monetary news and the feedback from stock returns to policy expectations using data from days with FOMC announcements. We do not find that the response of the stock market to scheduled Fed policy announcements is state dependent.

Similar to our analysis, other studies using identification through heteroskedasticity use subsets of the time series data for the markets they analyze.[24] It is also worth noting that our estimation approach is simpler and easier to implement than the methodologies used by these studies. For example, the estimation in Ehrmann et al. (2011) relies on estimated volatility regimes and on multiple coefficient restrictions. The estimation approach in Andersen et al. (2007) is based on conditional heteroskedasticity and assumes that return innovations are conditionally uncorrelated after accounting for measurable news in scheduled macroeconomic announcements. In contrast, our approach uses known volatility regimes, accepts that all relevant macroeconomic developments that induce comovement in asset returns are inherently difficult to measure and obviates the need to measure them. Our identification approach taking advantage of the predictable changes in intraday return volatility can be used to analyze other markets and answer other empirical questions.

[24] For example, see Andersen et al. (2007) and Ehrmann, Fratzscher, and Rigobon (2011).

References

Aastveit, K. A., Furlanetto, F., Loria, F. (2017). Has the Fed responded to house and stock prices? A time-varying analysis. Banco de Espana Working Paper No. 1713.

Andersen, T. G., Bollerslev, T., Diebold, F. X., Vega, C. (2007). Real-time price discovery in stock, bond and foreign exchange markets. *Journal of International Economics*, 73, 251-277.

Barclay, M. J., Warner, J. B. (1993). Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics*, 34, 281-305.

Basistha, A., Kurov, A. (2008). Macroeconomic cycles and the stock market's reaction to monetary policy. *Journal of Banking and Finance*, 32, 2606-2616.

Bekaert, G., Hoerova, M., Lo Duca, M. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60, 771-788.

Bekaert, G., Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, 183, 181-192.

Bernanke, B. (2002). Asset-price "bubbles" and monetary policy. Remarks before the New York Chapter of the National Association for Business Economics, New York. http://www.federalreserve.gov/boarddocs/speeches/2002/20021015/default.htm.

Bernanke, B. S., Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy? *Journal of Finance*, 60, 1221-1257.

Birru, J., Figlewski, S. (2010). The impact of the Federal Reserve's interest rate target announcement on stock prices: A closer look at how the market impounds new information, Working paper, New York University.

Bjørnland, H. C., Leitemo, K. (2009). Identifying the interdependence between U.S. monetary policy and the stock market. *Journal of Monetary Economics*, 56, 275-282.

Bunzel, H., Enders, W. (2010). The Taylor rule and "opportunistic" monetary policy. *Journal of Money, Credit and Banking*, 42, 931-949.

Chen, S. (2007). Does monetary policy have asymmetric effects on stock returns? *Journal of Money, Credit and Banking*, 39, 667-688.

Cheng, L. T. W., Jiang, L., Ng, R. W. Y. (2004). Information content of extended trading for index futures. *Journal of Futures Markets*, 24, 861-886.

Cieslak, A., Vissing-Jorgensen, A. (2021). The economics of the Fed put. *Review of Financial Studies*, 34, 4045-4089.

Cieslak, A., Morse, A., Vissing-Jorgensen, A. (2019). Stock returns over the FOMC cycle. *Journal of Finance*, 74, 2201-2248.

Cochrane, J. Y., Piazzesi, M. (2002). The fed and interest rates: A high-frequency identification. *American Economic Review*, 92, 90-95.

Cremers, M., Fleckenstein, M., Gandhi, P. (2021). Treasury yield implied volatility and real activity. *Journal of Financial Economics*, 140, 412-435.

D'Amico, S., & Farka, M. (2011). The Fed and the stock market: An identification based on intraday futures data. *Journal of Business & Economic Statistics*, 29, 126-137.

Ederington, L. H., Lee, J. H. (1995). The short-run dynamics of the price adjustment to new information. *Journal of Financial and Quantitative Analysis*, 30, 117-134.

Ehrmann, M., Fratzscher, M. (2004). Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit, and Banking*, 36, 719-737.

Ehrmann, M., Fratzscher, M., Rigobon. R. (2011). Stocks, bonds, money markets and exchange rates: Measuring international financial transmission. *Journal of Applied Econometrics*, 26, 948-974.

Evans, M., Lyons, R. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy*, 110, 170-180.

Fleming, M., Piazzesi, M. (2005). Monetary policy tick-by-tick. Working paper, Federal Reserve Bank of New York.

French, F., Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17, 5-26.

Furlanetto, F. (2011). Does monetary policy react to asset prices? Some international evidence. *International Journal of Central Banking*, 7, 91-111.

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

Gilchrist, S., Zakrajšek, E. (2013). The impact of the Federal Reserve's large-scale asset purchase programs on corporate credit risk. *Journal of Money, Credit and Banking*, 45, 29-57.

Gu, C., Kurov, A., Wolfe, M. H. (2018). Relief rallies after FOMC announcements as a resolution of uncertainty. *Journal of Empirical Finance*, 49, 1-18.

Gürkaynak, R. S., Sack, B., Swanson, E. (2005). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking*, 1, 55-93.

Gürkaynak, R. S., Sack, B., Swanson, E. (2007). Market-based measures of monetary policy expectations. *Journal of Business and Economic Statistics*, 25, 201-212.

Hanson, S. G., Stein, J. C. (2015). Monetary policy and long-term real rates. *Journal of Financial Economics*, 115, 429-448.

Holden, C. W., Subrahmanyam, A. (1992). Long-lived private information and imperfect competition. *Journal of Finance*, 47, 247-270.

Huang, R. D. (2002). The quality of ECN and Nasdaq market maker quotes. *Journal of Finance*, 57, 1285-1319.

Kontonikas, A., MacDonald, R., Saggu, A. (2013). Stock market reaction to fed funds rate surprises: State dependence and the financial crisis. *Journal of Banking and Finance,* 37, 4025-4037.

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review*, 43, 107-127.

Kurov, A. (2010). Investor sentiment and the stock market's reaction to monetary policy, *Journal of Banking and Finance*, 34, 139-149.

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

Lee, B. S. (1992). Causal relations among stock returns, interest rates, real activity, and inflation. *Journal of Finance*, 47, 1591-1603.

Lunde, A., Timmermann, A. G. (2004). Duration dependence in stock prices: An analysis of bull and bear markets. *Journal of Business & Economic Statistics*, 22, 253-273.

Lütkepohl, H. (2013). Identifying structural vector autoregressions via changes in volatility. In VAR models in macroeconomics – New developments and applications: Essays in honor of Christopher A. Sims (pp. 169-203). Emerald Group Publishing Limited.

Maheu, J. M., McCurdy, T. H., Song, Y. (2012). Components of bull and bear markets: Bull corrections and bear rallies. *Journal of Business & Economic Statistics*, 30, 391-403.

Menkveld, A., Sarkar, A., van der Wel, M. (2012). Customer order flow, intermediaries, and discovery of the equilibrium risk-free rate, *Journal of Financial and Quantitative Analysis*, 47, 821-849.

Pagan, A. R., Sossounov, K. A. (2003). A simple framework for analysing bull and bear markets. *Journal of Applied Econometrics*, 18, 23-46.

Paul, P. (2020). The time-varying effect of monetary policy on asset prices. *Review of Economics and Statistics*, 102, 690-704.

Pavasuthipaisit, R. (2010). The role of asset prices in best-practice monetary policy. *International Journal of Central Banking*, 6, 81-115.

Piazzesi, M., Swanson, E. T. (2008). Futures prices as risk-adjusted forecasts of monetary policy. *Journal of Monetary Economics,* 55, 677-691.

Poole, W. (2008). Market bailouts and the "Fed put." *Federal Reserve Bank of St. Louis Review*, 90, 65-74.

Ravn, S. H. (2012). Has the Fed reacted asymmetrically to stock prices? *The B.E. Journal of Macroeconomics*, 12, 1-36.

Rigobon, R., Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *Quarterly Journal of Economics,* 118, 639-669.

Rigobon, R., Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics,* 51, 1553-1575.

Roubini, N. (2006). Why central banks should burst bubbles. *International Finance*, 9, 87-107.

Schwert, G. W. (1989). Why does stock market volatility change over time? *Journal of Finance*, 44, 1115-1153.

Wongswan, J. (2009). The response of global equity indexes to U.S. monetary policy announcements. *Journal of International Money and Finance*, 28, 344-365.

Table 1
Response of monetary policy expectations to stock returns

	Full Sample
Policy response (β)	0.0068***
	(0.0008)
Heteroskedasticity parameter (λ)	0.0464***
	(0.0034)
Test of overidentifying restrictions	0.5048
N	5,675

The sample period is from October 1997 through December 2019. The parameters are estimated using GMM. Standard errors are shown in parentheses. p-value is shown for the test of overidentifying restrictions. *** indicates statistical significance at 1% levels.

Table 2
Response of monetary policy expectations to stock returns during expansions and recessions

Panel A. Expansions and recessions in the full sample period

	Recessions	Expansions	Difference in coefficients (Recession – Expansion)
Policy response (β)	0.0108***	0.0053***	0.0055***
	(0.0018)	(0.0006)	(0.0019)
Heteroskedasticity parameter (λ)	0.1364***	0.0367***	
	(0.0257)	(0.0019)	
Test of overidentifying restrictions	0.2861	0.9670	
N	547	5,128	

Panel B. Expansions and recessions excluding the zero lower bound period

	Recessions	Expansions	Difference in coefficients (Recession – Expansion)
Policy response (β)	0.0133***	0.0077***	0.0056**
	(0.0023)	(0.0009)	(0.0025)
Heteroskedasticity parameter (λ)	0.1308***	0.0339***	
	(0.0321)	(0.0022)	
Test of overidentifying restrictions	0.3237	0.8698	
N	410	3,459	

Panel C. Expansions and recession under *conventional* monetary policy (October 1997 – December 2007)

	Recession	Expansion	Difference in coefficients (Recession – Expansion)
Policy response (β)	0.0116***	0.0081***	0.0035
	(0.0044)	(0.0011)	(0.0045)
Heteroskedasticity parameter (λ)	0.0453***	0.0376***	
	(0.0099)	(0.0028)	
Test of overidentifying restrictions	0.2689	0.9718	
N	163	2,422	

Panel D. Expansion and recession under *unconventional* monetary policy (Jan. 2008 – Dec. 2019)

	Recession	Expansion	Difference in coefficients (Recession – Expansion)
Policy response (β)	0.0107***	0.0025***	0.0082***
	(0.0020)	(0.0005)	(0.0020)
Heteroskedasticity parameter (λ)	0.1764***	0.0358***	
	(0.0352)	(0.0024)	
Test of overidentifying restrictions	0.3898	0.5214	
N	384	2,706	

The full sample period is from October 1997 through December 2019. The recessions are from April 2001 to November 2001 and from January 2008 through June 2009. The recessions are based on the NBER business cycle dates. Panel B excludes the period from December 16, 2008 to December 16, 2015. The parameters are estimated using GMM. Standard errors are shown in parentheses. *p*-values are shown for the test of overidentifying restrictions. Standard normal critical values are used to test whether the difference between coefficients in expansion and recession is statistically significant. ** and *** indicate statistical significance at 5% and 1% levels, respectively.

Table 3
Response of monetary policy expectations to stock returns during bull and bear markets

Panel A. Bull and bear markets in the full sample period

	Bear markets	Bull markets	Difference in coefficients (Bear – Bull)
Policy response (β)	0.0114***	0.0036***	0.0079***
	(0.0014)	(0.0005)	(0.0015)
Heteroskedasticity parameter (λ)	0.1071***	0.0333***	
	(0.0155)	(0.0017)	
Test of overidentifying restrictions	0.3877	0.4625	
N	1,005	4,670	

Panel B. Bull and bear markets excluding the zero lower bound period

	Bear markets	Bull markets	Difference in coefficients (Bear – Bull)
Policy response (β)	0.0126***	0.0057***	0.0069***
	(0.0016)	(0.0009)	(0.0018)
Heteroskedasticity parameter (λ)	0.0983***	0.0271***	
	(0.0159)	(0.0017)	
Test of overidentifying restrictions	0.3799	0.6782	
N	932	2,937	

Panel C. Bull and bear markets under *conventional* monetary policy (October 1997 – December 2007)

	Bear markets	Bull markets	Difference in coefficients (Bear – Bull)
Policy response (β)	0.0116***	0.0056***	0.0059***
	(0.0016)	(0.0012)	(0.0021)
Heteroskedasticity parameter (λ)	0.0661***	0.0282***	
	(0.0079)	(0.0020)	
Test of overidentifying restrictions	0.6038	0.8015	
N	685	1,900	

Panel D. Bull and bear markets under *unconventional* monetary policy (Jan. 2008 – Dec. 2019)

	Bear markets	Bull markets	Difference in coefficients (Bear – Bull)
Policy response (β)	0.0114***	0.0025***	0.0089***
	(0.0021)	(0.0005)	(0.0021)
Heteroskedasticity parameter (λ)	0.1965***	0.0367***	
	(0.0416)	(0.0024)	
Test of overidentifying restrictions	0.4628	0.3092	
N	320	2,770	

The full sample period is from October 1997 through December 2019. Panel B excludes the period from December 16, 2008 to December 16, 2015. Bull and bear markets are classified with Pagan and Sossounov (2003) algorithm. The bear market periods are from April 2000 to October 2002 and from November 2007 to March 2009. The parameters are estimated using GMM. Standard errors are shown in parentheses. *p*-values are shown for the test of overidentifying restrictions. Standard normal critical values are used to test whether the difference between coefficients in bull and bear markets is statistically significant. *** indicates statistical significance at 1% level.

Table 4
Relation between stock returns and monetary policy expectations on FOMC meeting days

Panel A. Response of monetary policy expectations to stock returns and response of stock returns to monetary policy shocks in expansions and recessions

	Recessions	Expansions	Difference in coefficients (Recession – Expansion)
Policy response to stock returns (β)	0.0138**	0.0002	0.0136**
	(0.0054)	(0.0020)	(0.0057)
Response of stock returns to policy shocks (α)	-5.4696***	-7.3500***	1.8804
	(1.2630)	(1.2161)	(1.7533)
Heteroskedasticity parameter 1 $\left(\Delta_{\eta}^{open}\right)$	0.0858	0.0377***	
	(0.0734)	(0.0127)	
Heteroskedasticity parameter 2 $(\Delta_{\varepsilon}^{FOMC})$	0.0112**	0.0012***	
	(0.0039)	(0.0003)	
Heteroskedasticity parameter 3 $\left(\Delta_{\eta}^{FOMC}\right)$	0.2810*	0.1230***	
	(0.1345)	(0.0234)	
Test of overidentifying restrictions	0.2749	0.3424	
N	17	161	

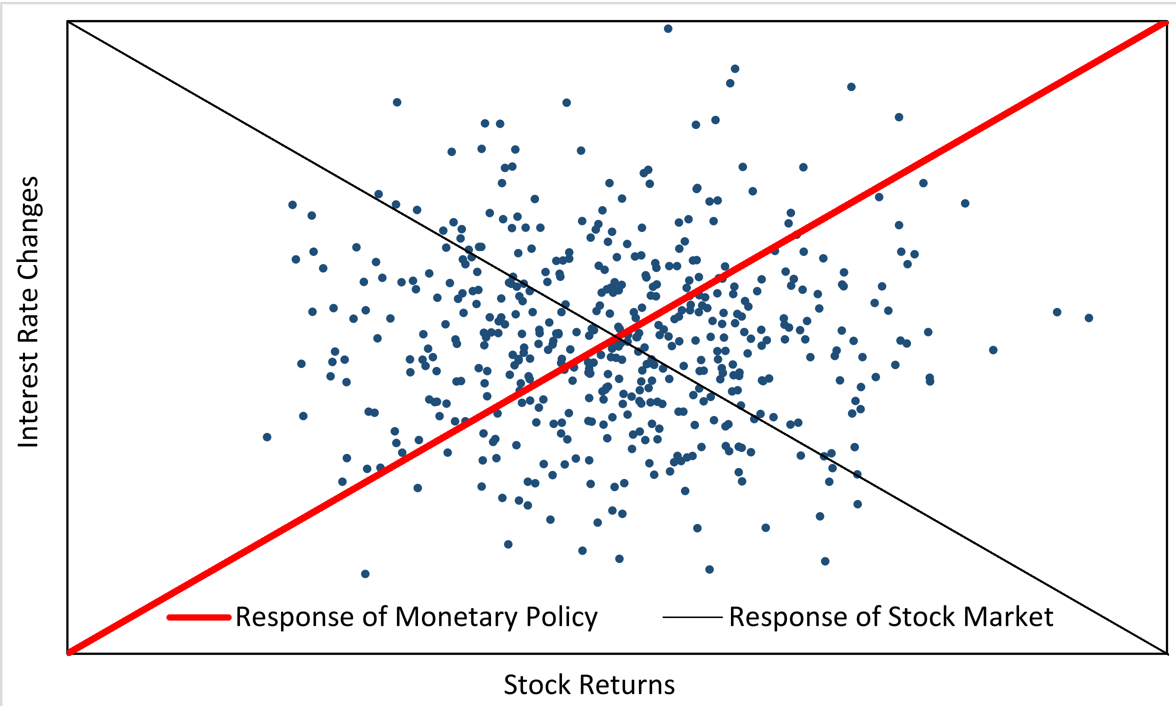
Panel B. Response of monetary policy expectations to stock returns and response of stock returns to monetary policy shocks in bull and bear markets

	Bear markets	Bull markets	Difference in coefficients (Bear – Bull)
Policy response to stock returns (β)	0.0106**	-0.0001	0.0107**
	(0.0051)	(0.0016)	(0.0053)
Response of stock returns to policy shocks (α)	-5.8135***	-7.4007***	1.5871
	(1.3564)	(1.2515)	(1.8456)
Heteroskedasticity parameter 1 $\left(\Delta_{\eta}^{open}\right)$	0.0709	0.0358***	
	(0.0420)	(0.0136)	
Heteroskedasticity parameter 2 $(\Delta_{\varepsilon}^{FOMC})$	0.0071***	0.0010***	
	(0.0024)	(0.0003)	
Heteroskedasticity parameter 3 $\left(\Delta_{\eta}^{FOMC}\right)$	0.2945***	0.1062***	
	(0.1031)	(0.0192)	
Test of overidentifying restrictions	0.3072	0.4267	
N	31	147	

The full sample period is from October 1997 through December 2019. All estimations include only data for days of scheduled FOMC announcements. The recessions are from April 2001 to November 2001 and from January 2008 through June 2009. The recessions are based on the NBER business cycle dates. The bear market periods are from April 2000 to October 2002 and from November 2007 to March 2009. Bear markets are classified with Pagan and Sossounov (2003) algorithm. The parameters are estimated using GMM. Standard errors are shown in parentheses. p-values are shown for the test of overidentifying restrictions. Standard normal critical values are used to test whether the difference between coefficients is statistically significant. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Figure 1
Illustration of the identification problem in the relation between stock returns and interest rate changes

Panel A: Simultaneity in the relation between stock returns and interest rate changes



Panel B: Times of higher stock return volatility

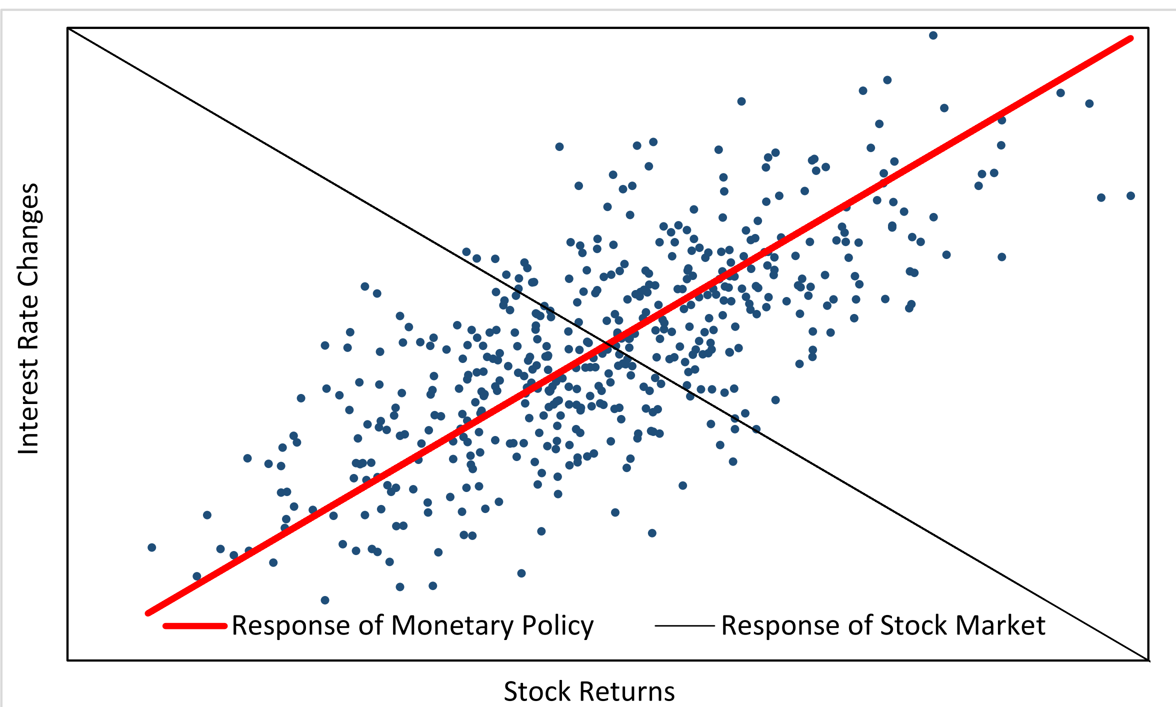
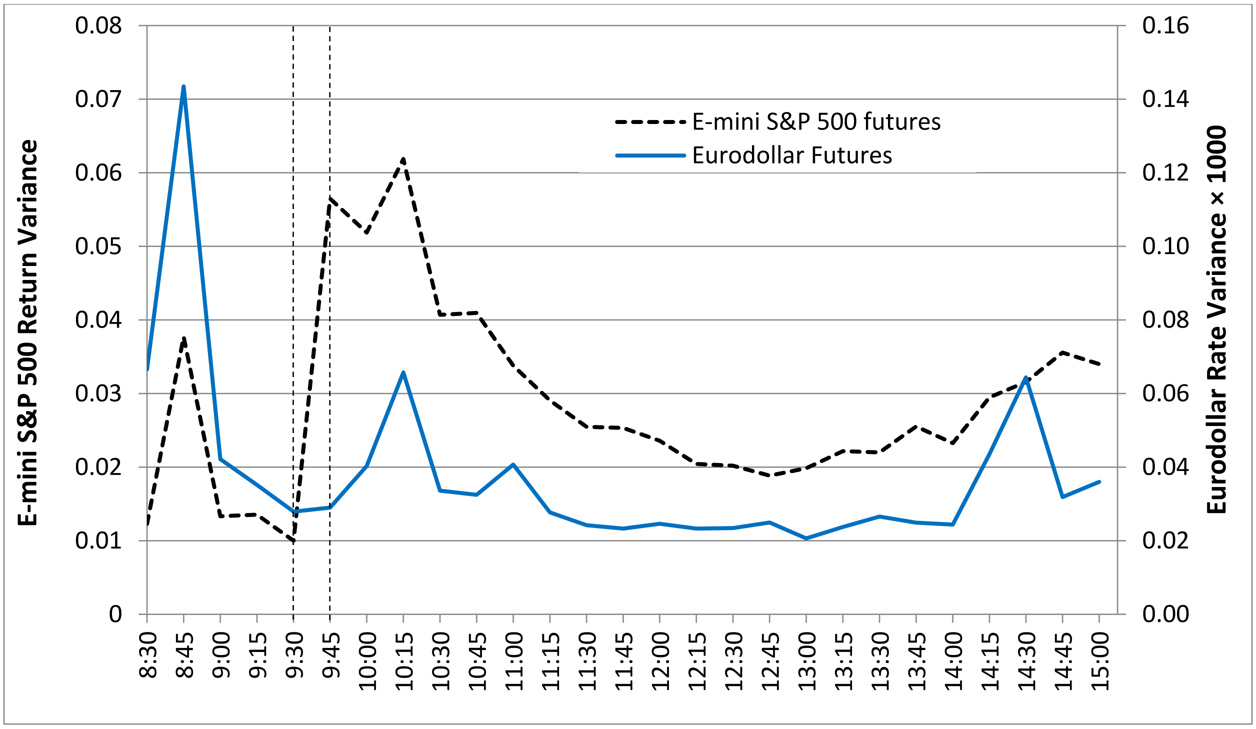
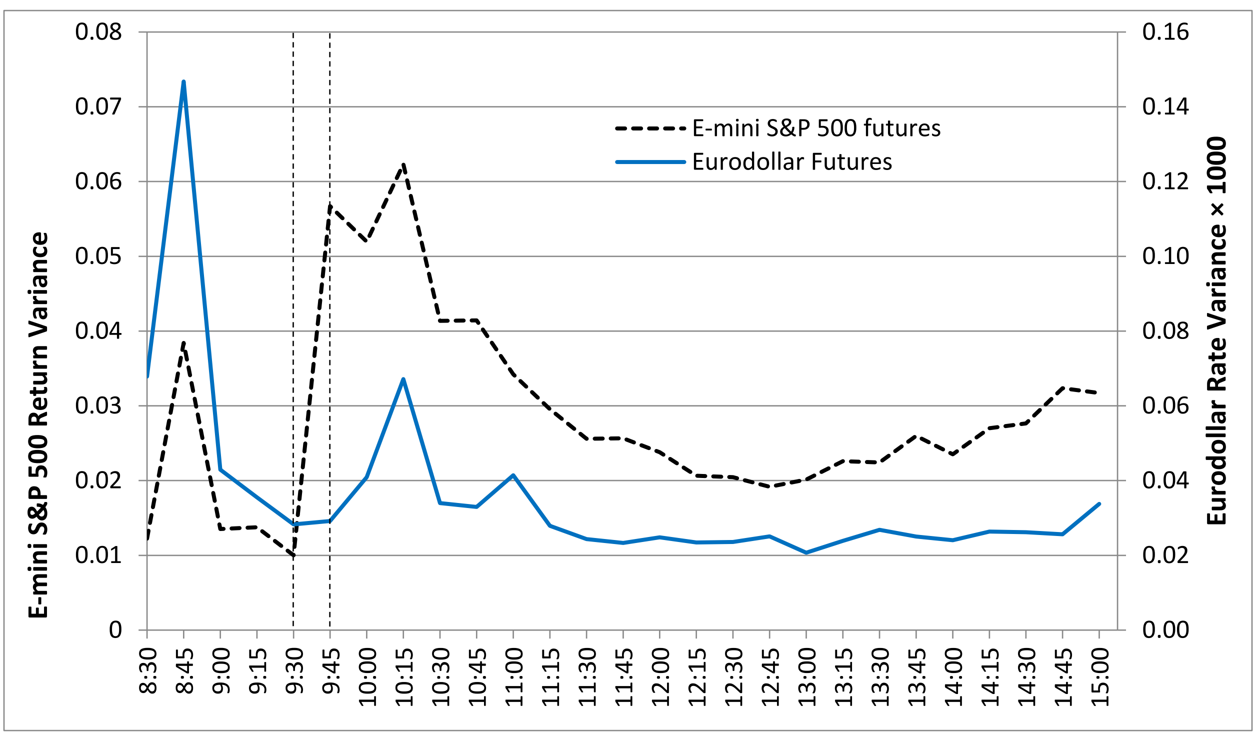


Figure 2
Intraday periodicity in volatility and comovement of index futures returns and Eurodollar futures rate changes

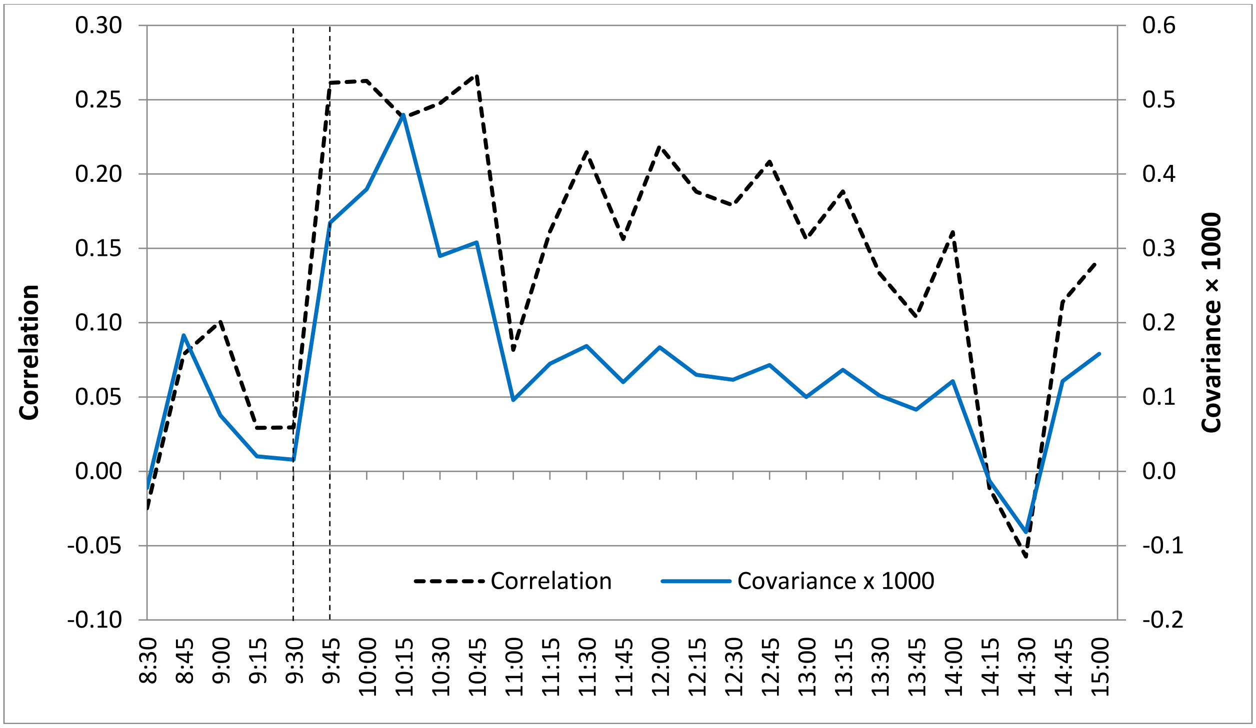
Panel A1: Variance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes



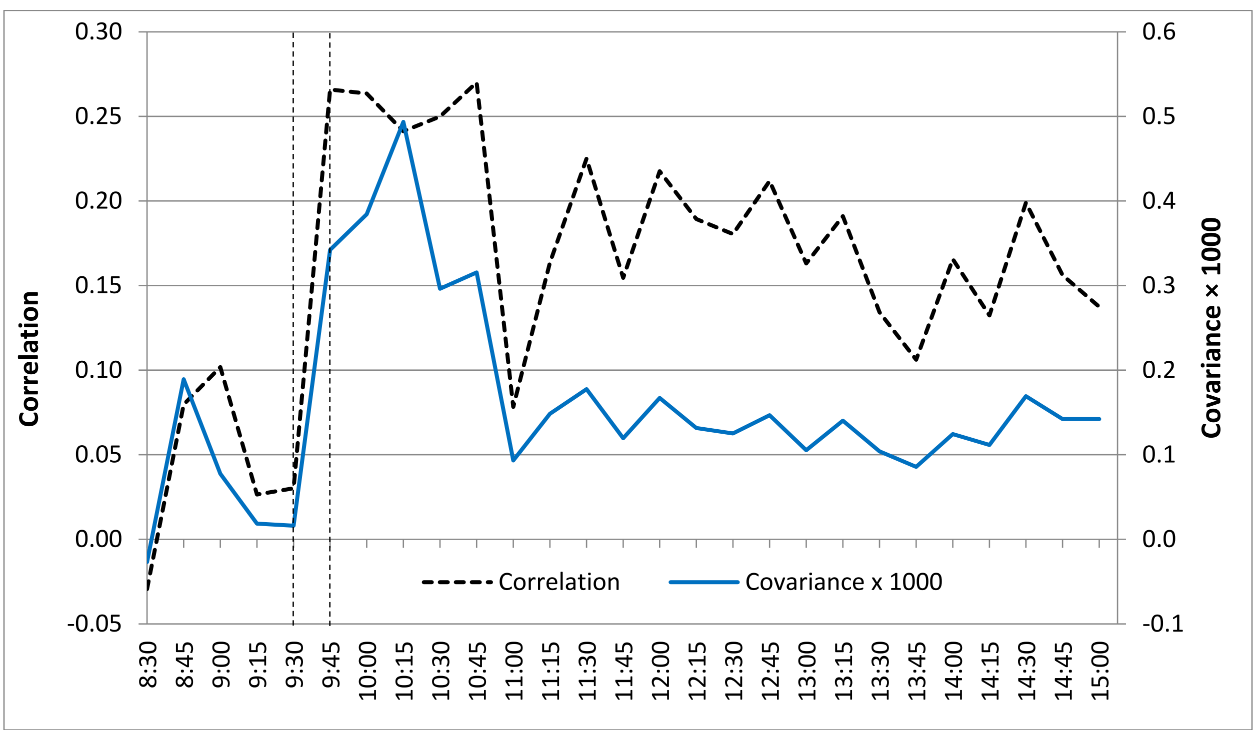
Panel A2: Variance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes excluding FOMC announcement days



Panel B1. Correlation and covariance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes



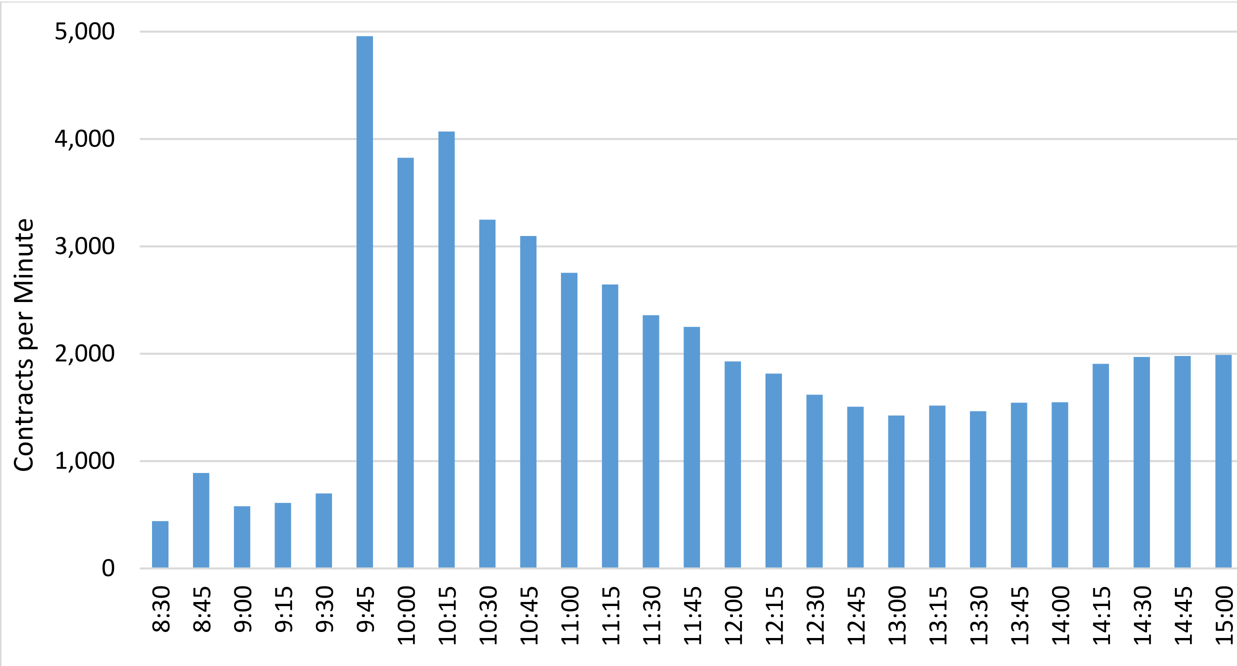
Panel B2: Correlation and covariance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes excluding FOMC announcement days



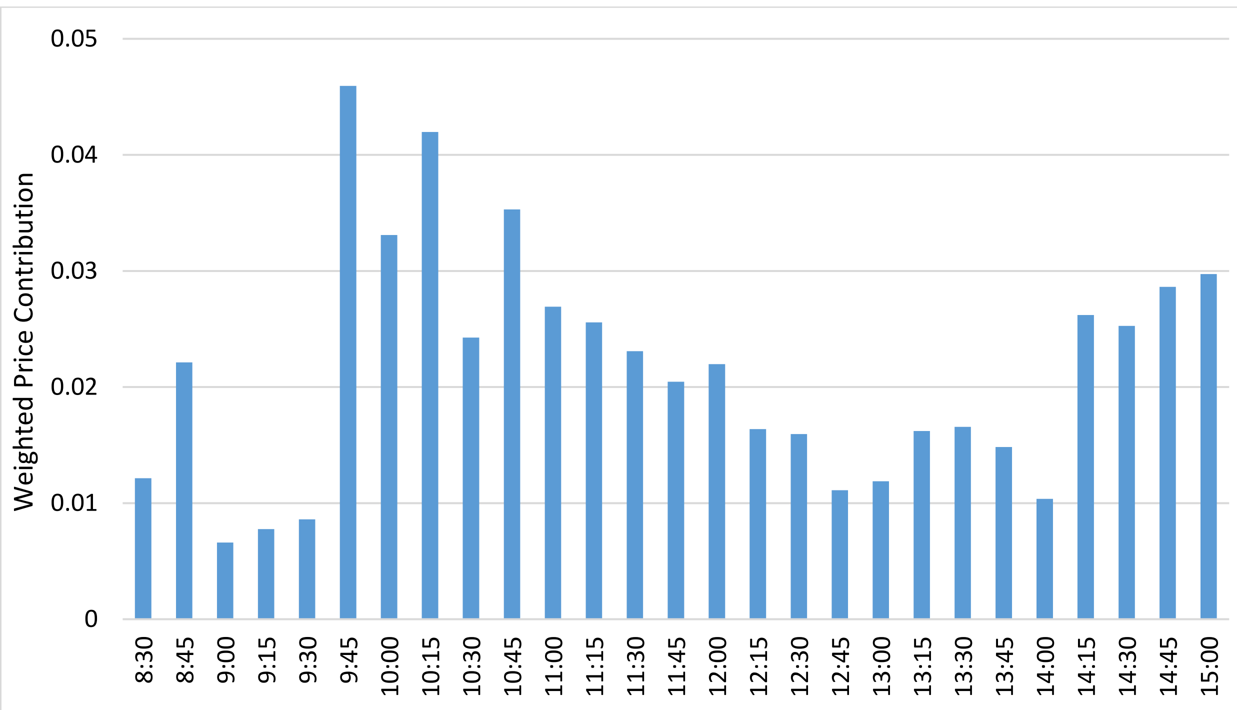
The sample period is from October 1, 1997 to December 31, 2019. The statistics are computed for residuals from a VAR model of 15-minute E-mini S&P 500 futures returns and Eurodollar futures rate changes. The model includes two lags of the two variables.

Figure 3
Average trading volume and weighted price contribution in the E-mini S&P 500 futures market by 15-minute interval

Panel A: Average trading volume



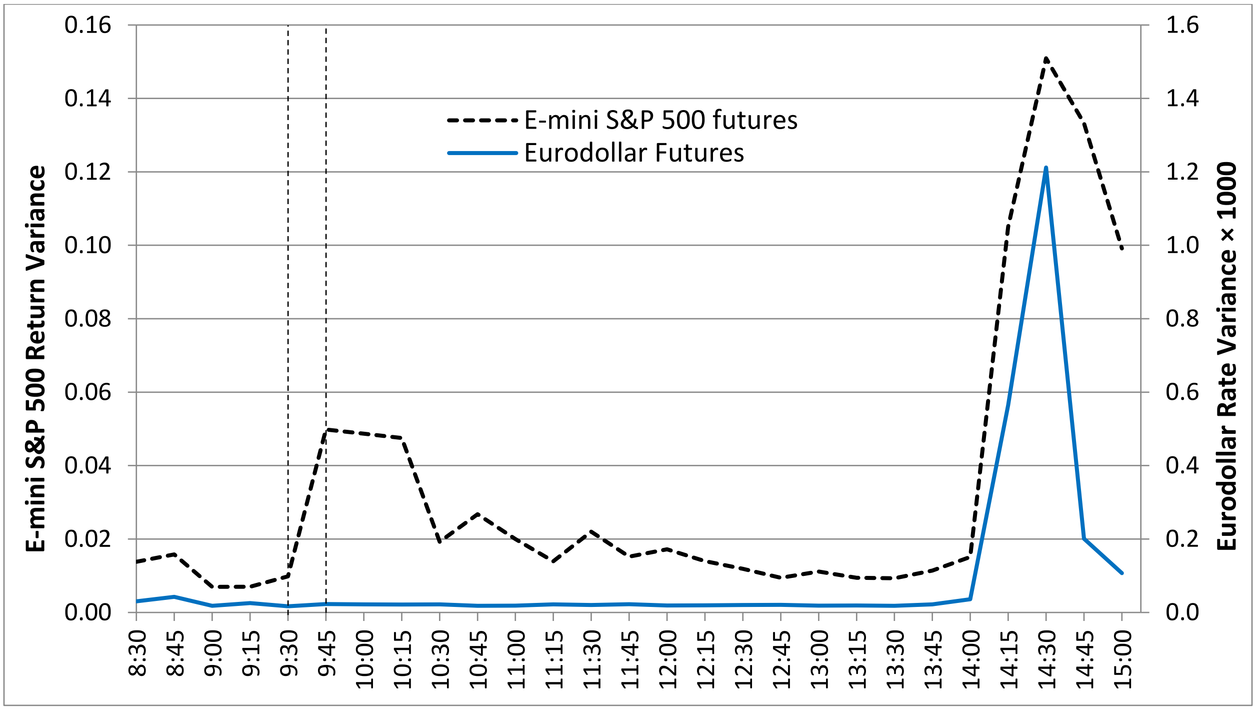
Panel B. Weighted price contribution



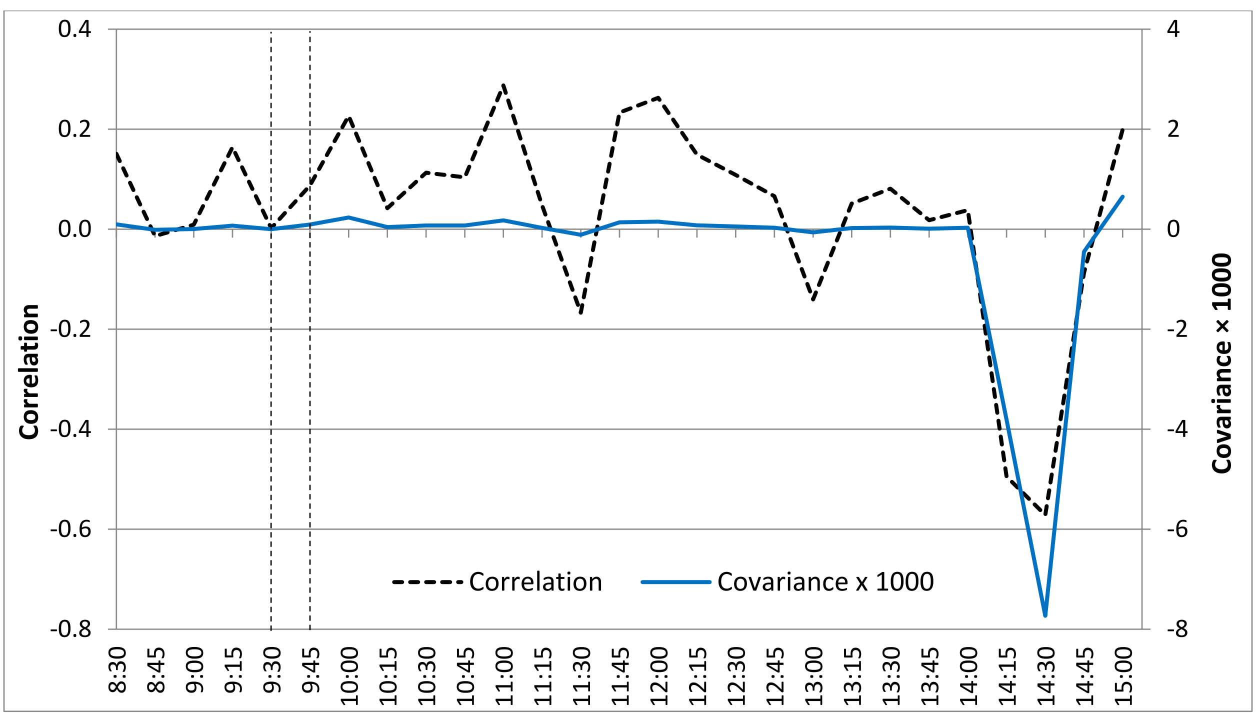
The sample period is from October 1, 1997 to December 31, 2019.

Figure 4
Intraday volatility and comovement of index futures returns and Eurodollar futures rate changes on days of FOMC meetings

Panel A: Variance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes



Panel B: Correlation and covariance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes



The sample period is from October 1, 1997 to December 31, 2019. The statistics shown are for residuals from a VAR model of 15-minute E-mini S&P 500 futures returns and Eurodollar futures rate changes.