When Does the Fed Care About Stock Prices?

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Abstract

We use a predictable change in the intraday volatility of index futures to identify the effect of stock returns on monetary policy. This identification approach relies on a weaker set of assumptions than required under identification through heteroskedasticity based on lower frequency data. Our identification approach also allows asymmetric responses and 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."

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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."
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> 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]
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> 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 easing of monetary policy in reaction to market declines has been labeled the "Fed put," often 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 (2020) 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] In this respect, understanding the link between monetary policy and the stock market is critical for monetary

[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.)

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 asset returns and monetary policy interest rates. The objective of this study is to examine the reaction of monetary policy to the stock market using a novel identification strategy.

The literature examining the Fed's response to the stock market is scant and the evidences are limited. Each such study must 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 simultaneity 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 vector autoregressive (VAR) model to account for the simultaneity of the interdependence between the stock market and the federal funds rate. The authors document that stock price shock leads to an increase in the interest rate in contrast to the findings of other VAR studies that do not count for the simultaneous interdependence (e.g., Lee, 1992).

In a more recent study, Cieslak and Vissing-Jorgensen (2020) employ textual analysis of FOMC minutes and transcripts to study the Fed put and find that intermeeting stock market returns predict the tone of the subsequent FOMC meetings. They show that the explanatory power of the negative tone of intermeeting stock market mentions for cuts to the Fed funds target rate is much

[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).

larger than that of any of 38 macroeconomic variables. Rigobon and Sack (2003) use identification through heteroscedasticity to estimate the reaction of monetary policy to the stock market by using shifts in volatility regimes 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, Lütkepohl (2013) highlights that identification through heteroskedasticity proposed in Rigobon and Sack (2003) depends upon the volatility regimes being known, which is usually not the case in practice.

Our work builds upon Rigobon and Sack (2003) in the following ways. First, our approach allows us to identify 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, in our approach we are not relying upon the volatility regimes being known, which is not realistic in practice (Lütkepohl, 2013). Instead, we exploit the intraday periodicity in volatility of index futures returns. Furthermore, our approach allows for a more granular study of the monetary policy response to stock returns by using time variation in volatility within each day. Specifically, in contrast to the approach in Rigobon and Sack (2003) that uses daily stock returns and interest rates, we benefit from intraday data and exploit the recurring upward shift in volatility of index futures returns at the stock market opening.

The main benefit of our approach is that the 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 shifts occur every day at the market opening, we can examine the response of monetary policy to the stock market in different macroeconomic environments. We are able to formally test whether the "Fed put" exists by estimating the Fed's response to the stock market 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).

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. Our approach is much easier to implement in practice than other identification through heteroskedasticity methods and can be applied in various contexts. In an online appendix, we show how to use our approach in to examine contemporaneous linkages between international markets and across asset classes. Our second contribution is empirical. We 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.[4]

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:

$$\Delta i_t = \beta R_t + \gamma z_t + \varepsilon_t \,, \tag{1}$$

$$R_t = \alpha \Delta i_t + z_t + \eta_t, \tag{2}$$

[4] 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.

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. Following Rigobon and Sack (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.

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.[5] 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

[5] 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.

(2007) show that Eurodollar futures provide good forecasts of the future fed funds rate.[6] 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.[7] 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-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 in this analysis 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.

[6] 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.
[7] 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.

2.2. Methodology: Identification through Heteroskedasticity

Rigobon and Sack (2003) propose using heteroskedasticity of the daily aggregate stock returns to estimate the response of monetary policy to the stock market. Using a sample period from 1985 to 1999, they show that the Federal Reserve 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. However, Furlanetto (2011) shows that this estimate is driven to a large extent by the Fed's reaction to the stock market crash in 1987 and finds no statistically significant reaction of monetary policy to stock returns over the 2003-2007 period. 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 dates of regime shifts have to be estimated, which negatively affects the reliability of the parameter estimates.

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.[8] 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.

[8] As a robustness check, we also used 30-minute intervals. The results were essentially unchanged.

to 3:00 p.m. ET.[9] 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.[10] 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 1 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 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 1 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.

[9] 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.

[10] 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.

Panel B1 in Figure 1 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 importance 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 1. 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 1 here]

Panel A in Figure 2 shows that the trading activity in the 15-minute interval ending at 9:45 a.m. increases by approximately a factor of seven 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) develop a model showing that trading on private information generated during non-trading hours is concentrated at the opening of the market. 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 an important 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 2 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.[11] 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 2 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.

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[11] See, for example, Huang (2002) and Cheng, Jiang and Ng (2004).

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 an increase in 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.[12] To obtain an estimator of the response of monetary policy to stock returns, equations (1) and (2) are written in reduced form as follows:

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

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

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:

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

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

[12] Most major scheduled U.S. macroeconomic announcements are made at 8:30 a.m. and 10:00 a.m. As Figure 1 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.

The difference between these covariance matrices is:

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

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 three moment conditions can be used 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.

It is useful to compare this 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.[13] 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.[14]

[13] 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.
[14] 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.

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 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 subsequently decompose our sample into expansionary and recessionary periods based on the NBER business cycle dates.[15] 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 *t*-test shown in the last column of Table 2 rejects the hypothesis that the response of monetary policy to stock returns is the same in expansions and recessions at the 1% significance 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

[15] 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. Second, the NBER recession dates also provide a reasonable date on which the Federal Reserve began to use unconventional methods to influence the economy. 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.

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. Note in Panel C, that in the 2001 recession, β is 0.0116 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 2001 recession as indicated by the estimates of λ.

Based on the β estimate for the 2001 recession, 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 0.0084. 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 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 first column displays the results from bear markets, the second column displays the results from bull markets, and the last column shows the difference between the coefficient estimates. The estimation results in Table 3 show that the response of monetary policy to the stock market approximately triples in bear markets compared to bull markets.

[Insert Table 3 here]

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 ($2.5/25 = 0.10$).

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.

Overall, our results are not consistent with the Fed "leaning against the wind" by trying to deflate stock market bubbles.[16] 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

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

economy. Our findings are also broadly consistent with Cieslak and Vissing-Jorgensen (2020) who use textual analysis of FOMC minutes and transcripts and show that negative intermeeting stocks 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 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 of such announcements during our sample period. Panel A1 of Figure 1 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 3 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 3 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 3 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.[17] 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 Eurodollar futures rate changes and the E-mini S&P 500 futures returns in the two 30-minute intervals is:

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

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

[17] 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.

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 3 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.[18] 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]

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

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 (2020) 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 (2020) argue through textual analysis of the FOMC minutes that the driver view is articulated more frequently by FOMC participants.

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 (2020) 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. This results in a muted response of policy expectations to stock returns on FOMC announcement days.

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.[19]

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 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

[19] 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.

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. Our results suggest that the "Fed put" likely depends on the state 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 unscheduled FOMC announcements 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 some 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 returns 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 the Fed policy news 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.[20] 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 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 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. In the online appendix, we provide two examples demonstrating how to use this approach to examine contemporaneous links between international stock markets and across different asset classes.

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

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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. A t-test is 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. A *t*-test is 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	

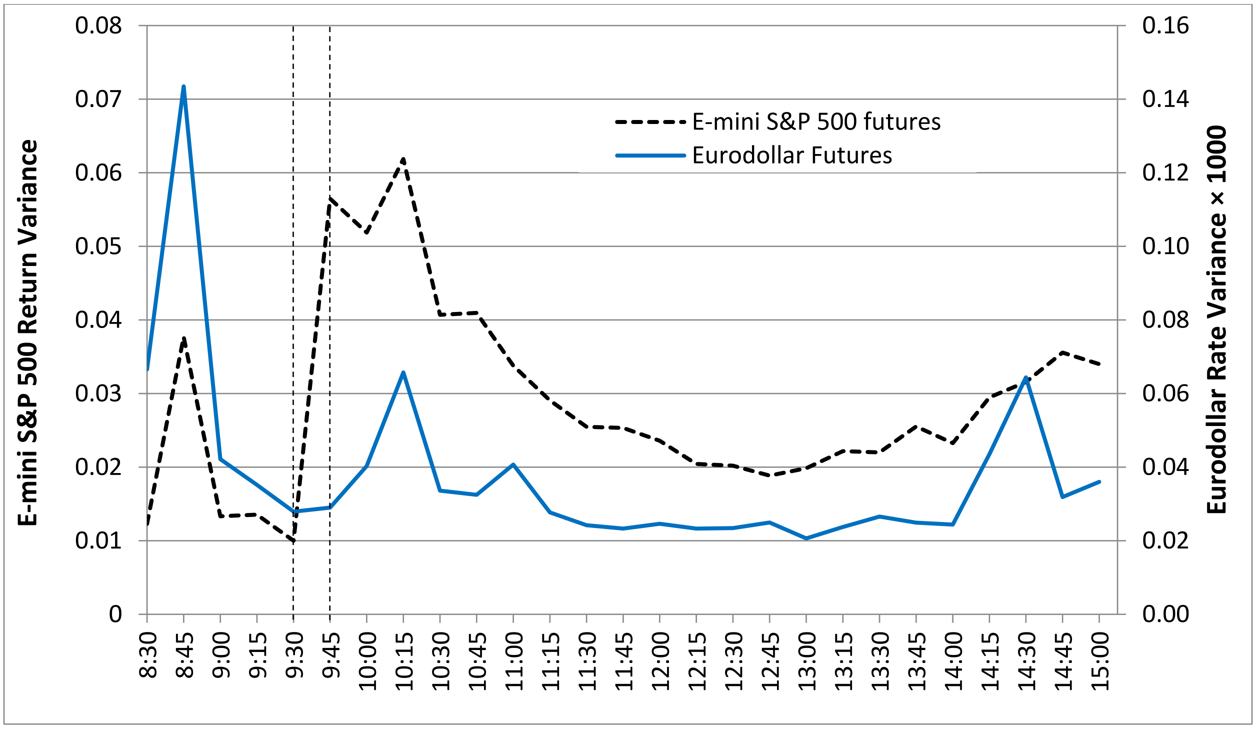
Panel B. Response of monetary policy expectations to stock returns and response of stock returns to monetary policy shocks in bull and bear markets

	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	

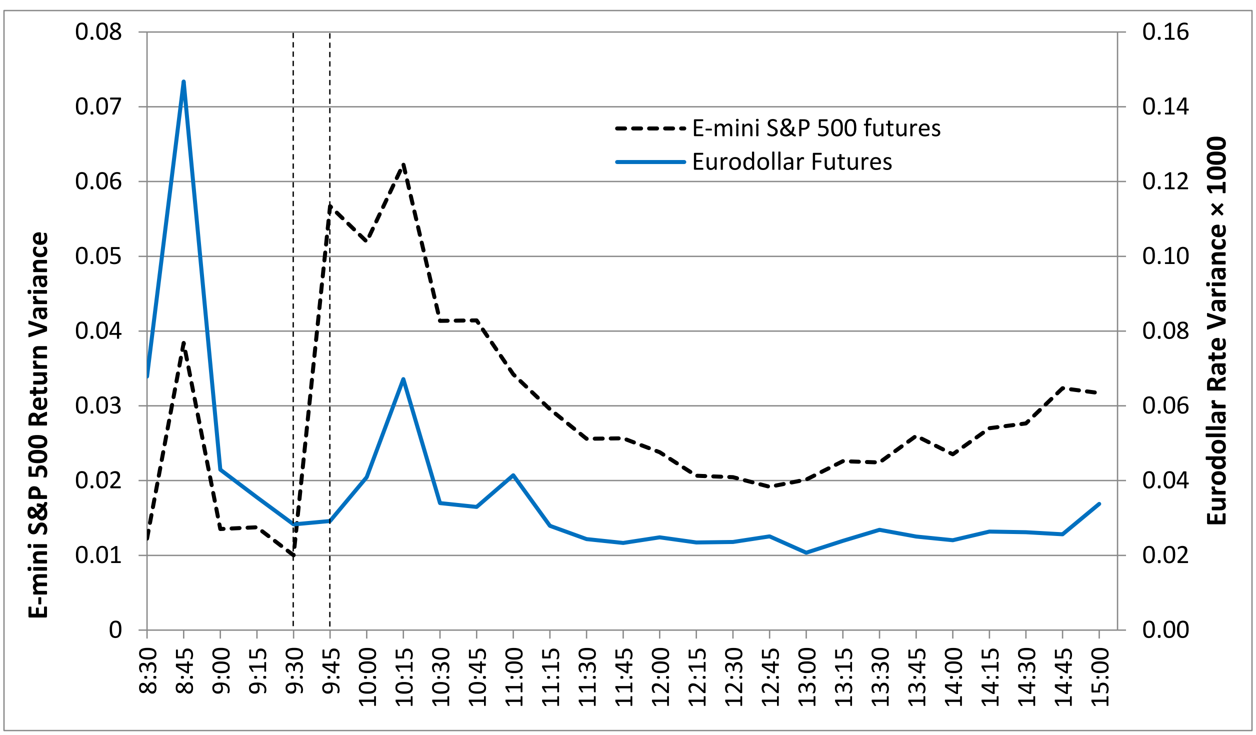
The full sample period is from October 1997 through December 2019. All estimations include only data for days of scheduled FOMC announcements. The recessions are from April 2001 to November 2001 and from January 2008 through June 2009. The recessions are based on the NBER business cycle dates. The bear 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. A t-test is used to test whether the difference in coefficients is statistically significant. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Figure 1
Intraday periodicity in volatility and comovement
of index futures returns and Eurodollar futures rate changes

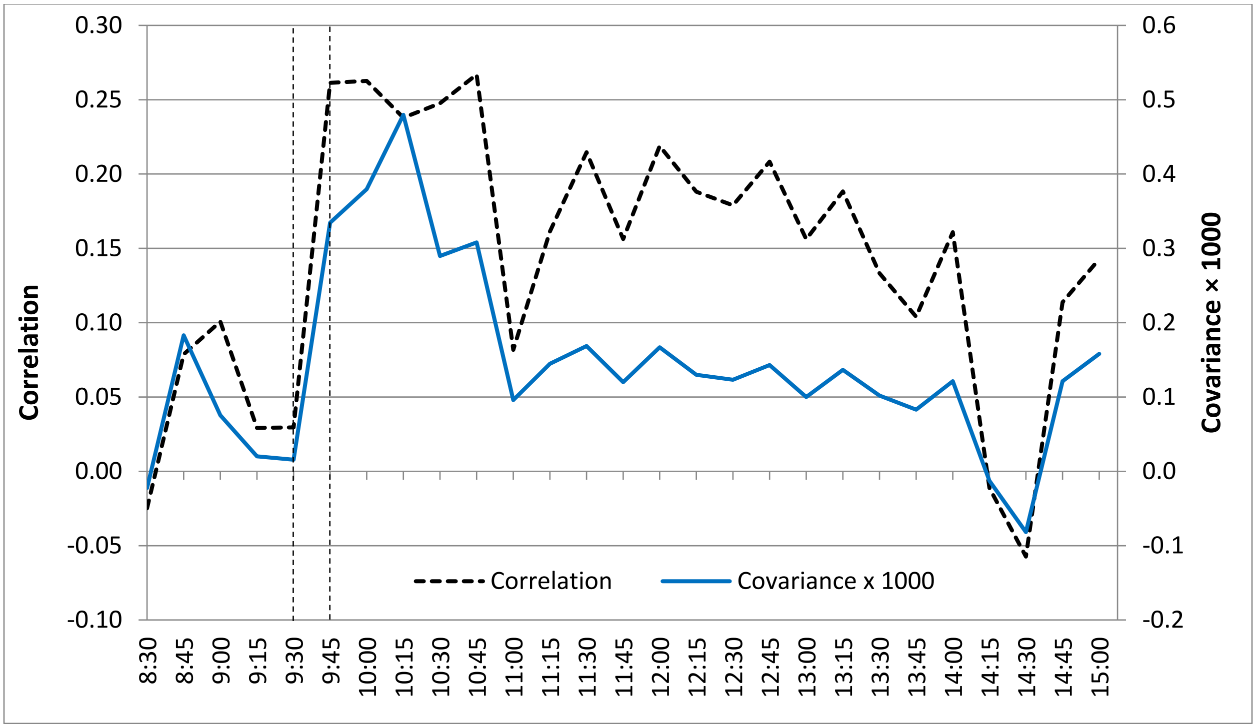
Panel A1: Variance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes



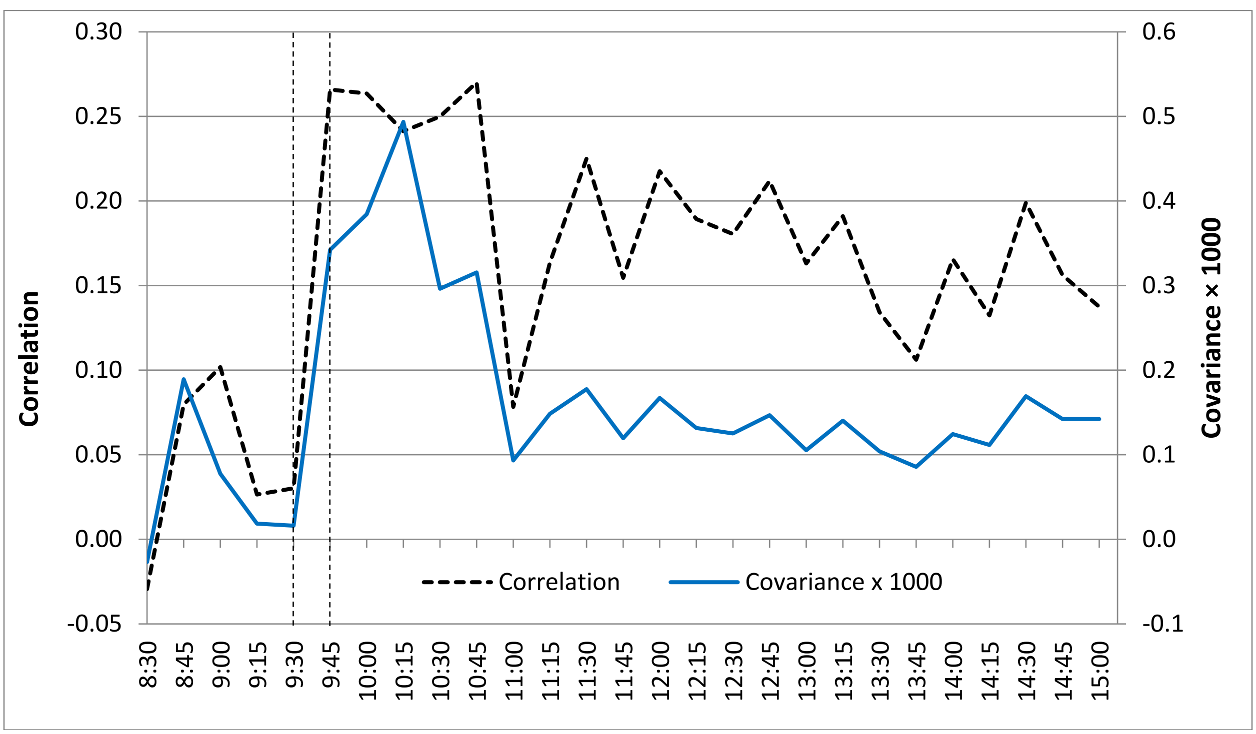
Panel A2: Variance of 15-minute E-mini S&P 500 returns
and Eurodollar futures rate changes excluding FOMC announcement days



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



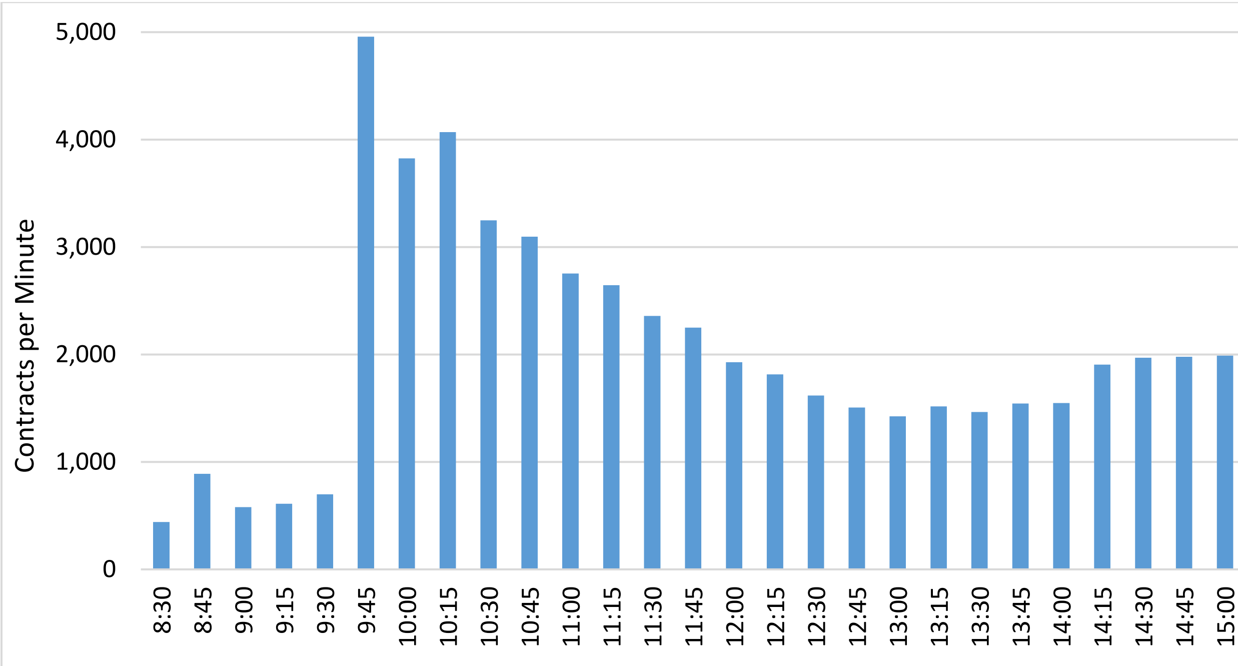
Panel B2: Correlation and covariance of 15-minute E-mini S&P 500 returns and Eurodollar futures rate changes excluding FOMC announcement days



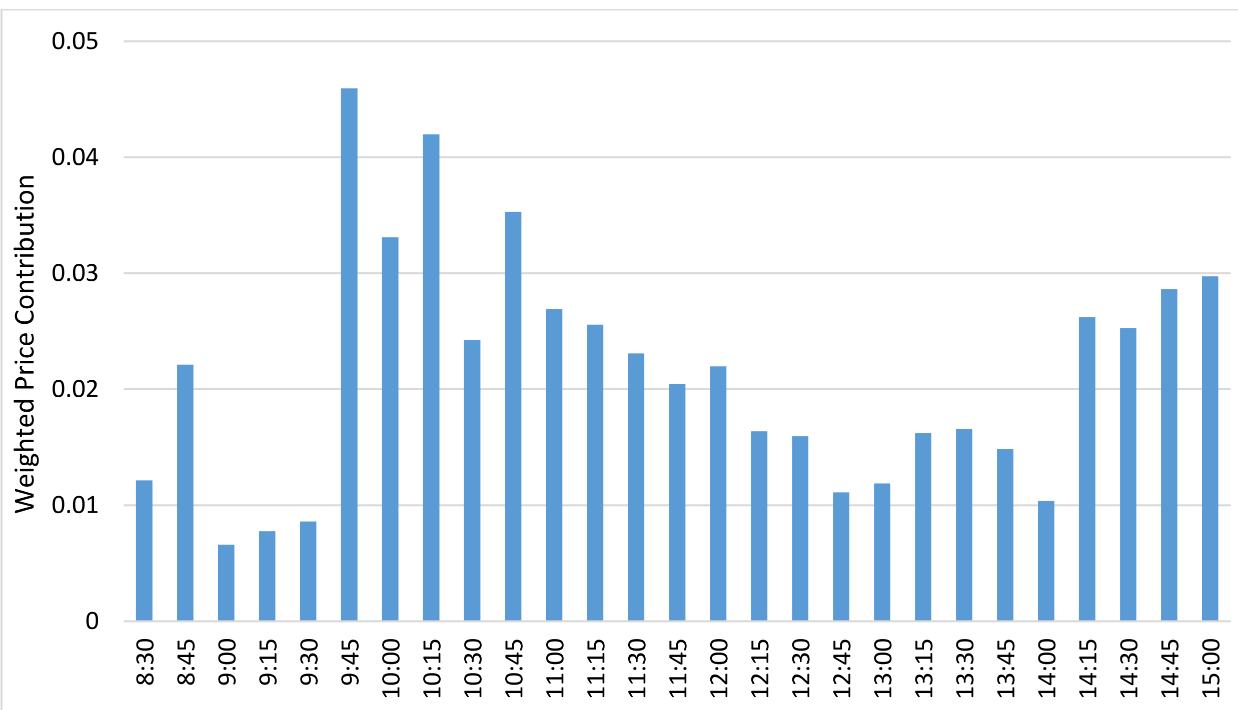
The sample period is from October 1, 1997 to December 31, 2019. The statistics are computed for residuals from a VAR model of 15-minute E-mini S&P 500 futures returns and Eurodollar futures rate changes. The model includes two lags of the two variables.

Figure 2
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



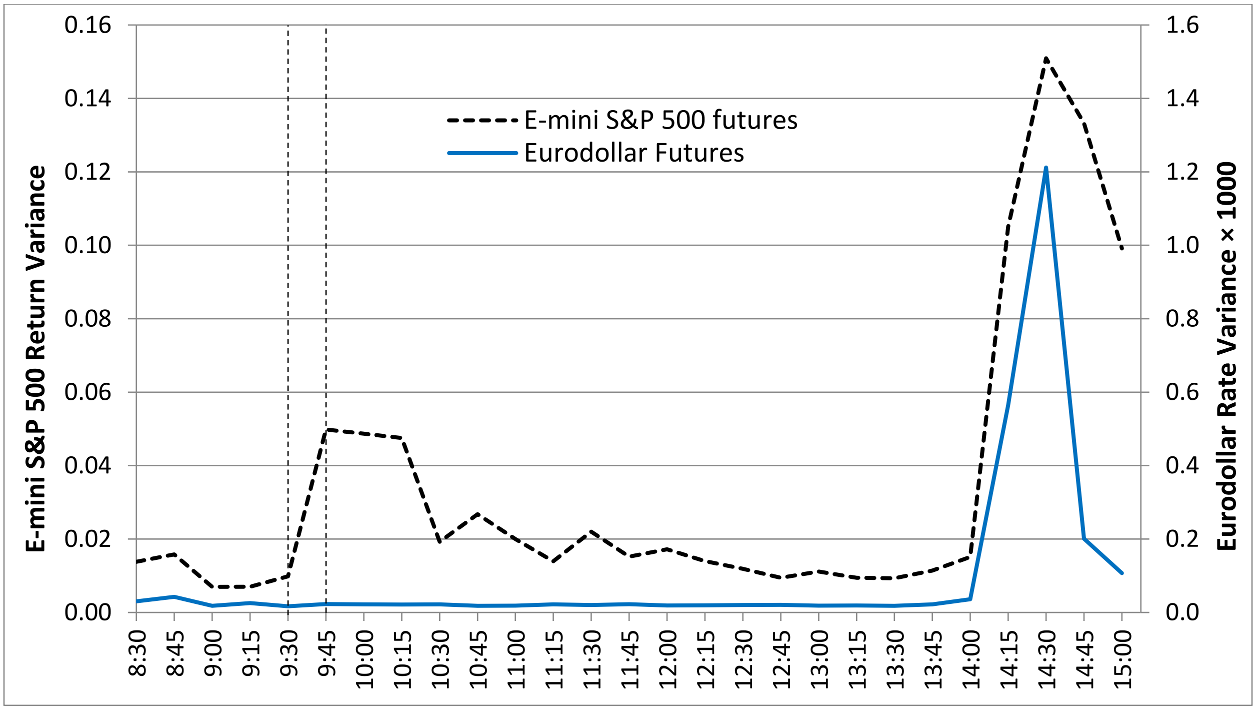
Panel B. Weighted price contribution



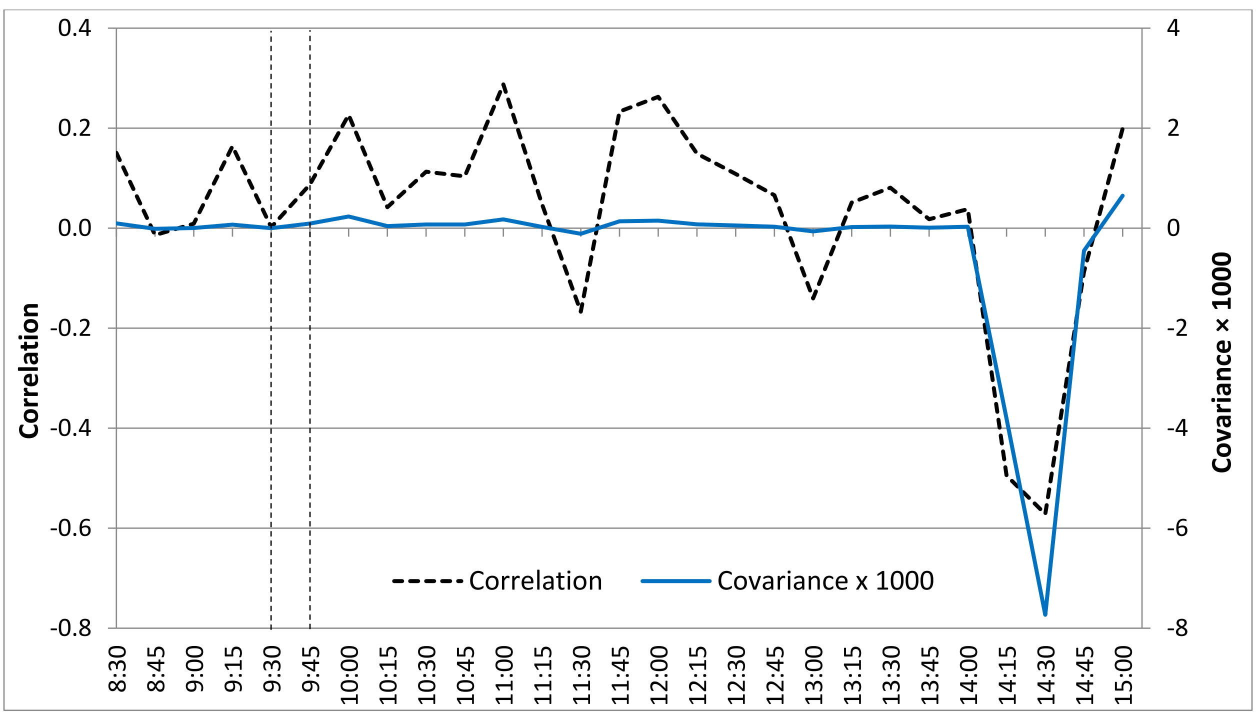
The sample period is from October 1, 1997 to December 31, 2019.

Figure 3
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.

Online Appendix

Examples of using similar identification through heteroskedasticity in other contexts

This appendix demonstrates that our identification approach can be applied in other settings. In the first example, we use it to examine contemporaneous linkages between international stock markets. In the second example, we apply it to measure contemporaneous interactions among multiple asset classes.

1. Analysis of contemporaneous links between international stock markets

Consider stock markets in three countries. These markets open and close at different times and have index futures contracts trading before the opening and after the close of the stock market. The contemporaneous interactions between index futures returns in these markets can be described using the following system of equations similar to equations (1) and (2) in the paper:

$$R_{1t} = a_{12}R_{2t} + a_{13}R_{3t} + b_1 z_t + \epsilon_{1t}, \tag{A1}$$

$$R_{2t} = a_{21}R_{1t} + a_{23}R_{3t} + b_2 z_t + \epsilon_{2t}, \tag{A2}$$

$$R_{3t} = a_{31}R_{1t} + a_{32}R_{2t} + z_t + \epsilon_{3t}, \tag{A3}$$

where R_{1t}, and R_{2t}, and R_{3t} are the index futures returns in countries 1, 2, and 3, respectively, z_t represents common macroeconomic shocks influencing the markets, and ϵ_{1t}, ϵ_{2t} and ϵ_{3t} are return innovations that are uncorrelated with each other and with the common shocks z_t. In matrix form, this system of three equations can be represented as:

$$\boldsymbol{AR_t} = \boldsymbol{B}z_t + \boldsymbol{\epsilon_t}. \tag{A4}$$

Similar to the relation between asset prices and interest rates examined in our paper, the effects of the three markets on one another (coefficients a_{ij}, $i \neq j$) cannot be estimated consistently with OLS due to simultaneity and omitted variables. Our approach of identification through heteroskedasticity using intraday futures data and taking advantage of the predictable changes in intraday return volatility offers a simple solution to this identification problem.

The times of the market opening and/or closing provide shifts in the covariance matrix of the index futures returns. These shifts are exogenous in the sense that they occur at the same time every trading day regardless of the economic or market conditions. Assuming that the coefficients measuring cross-market linkages a_{ij} and the variance of the common shocks σ_z remain stable around the times of these shifts, the change in the return covariance matrix around time S (market opening or closing) is:

$$\Delta_S \boldsymbol{\Omega} = \frac{1}{|\boldsymbol{A}|^2} \boldsymbol{C}(\boldsymbol{C}\boldsymbol{D}_{\boldsymbol{S}})^T, \tag{A5}$$

where $|\boldsymbol{A}|$ is the determinant of the market response coefficient matrix $\boldsymbol{A}$, $\boldsymbol{D}_{\boldsymbol{S}}$ is a diagonal matrix with the changes in the variance of return innovations of each market i around time S (Δ_{iS}) on the main diagonal, and $\boldsymbol{C}$ is the transpose of $\boldsymbol{A}$ s cofactor matrix. The elements of matrix $(c_{km}$, with $k, m \in \{1, 2, 3\})$ are functions of the market response coefficients a_{ij}. For example, $c_{11} = 1 - a_{23}a_{32}$, $c_{12} = a_{12} + a_{13}a_{32}$, etc. Thus, the elements of $\Delta_S \boldsymbol{\Omega}$ are made up of the market response coefficients and the changes in the variances of return innovations.

With one shift in the return covariance matrix, we have nine unknown parameters (six market response coefficients and three innovation variance changes) and six moment equations. Each additional shift in the covariance matrix provides six additional moment equations (three variance changes and three covariance changes of returns) with only three new parameters (changes in the variances of return innovations). We use three shifts in the covariance matrix (i.e., $S \in \{1, 2, 3\}$) that provide 18 moment equations with 15 unknown parameters (six market response coefficients and nine heteroskedasticity parameters). Therefore, the model is overidentified. We estimate the model parameters with GMM using the test of overidentifying restrictions to test the validity of our identification assumptions.

To provide an empirical illustration of this approach, we estimate the contemporaneous linkages between the stock markets in the U.S., the U.K. and Japan. Each of the three countries has index futures contracts actively trading both during and outside the regular trading hours of the country's stock market. We use index futures returns from October 1, 2015 to December 31, 2019.[21] During this period, the British FTSE-100 index futures traded on the Intercontinental Exchange (ICE) from 1:00 a.m. to 9:00 p.m. London time, and the E-mini S&P 500 and Nikkei-225 index futures traded on the Chicago Mercantile Exchange (CME) almost around the clock, with a break from 5:00 p.m. to 6:00 p.m. U.S. ET. The stock market in the U.S. opens at 9:30 a.m. U.S. ET, in the U.K. at 8:00 a.m. London time, and in Japan at 9 a.m. Tokyo time. We use 15-minute returns for the E-mini S&P 500, FTSE-100 and Nikkei-225 index futures from 1:00 a.m. to 9:00 p.m. London time when all of these three index futures contracts trade.

To remove return autocorrelation, we use residuals from a VAR that includes the 15-minute index futures returns for the three countries for the 20 hours from 8:00 p.m. U.S. ET to 4:00 p.m. U.S. ET on the following day. The VAR includes one lag of returns. The optimal lag length is determined using the Schwarz information criterion.[22] To remain consistent with the methodology in our paper, for the first covariance matrix shift we the two 15-minute intervals around the U.S. stock market opening at 9:30 a.m. U.S. ET. Panel A of Figure A1 shows large increases in volatility in all three index futures markets at that time. If we use the two 15-minute intervals that straddle the U.K. stock market opening at 8:00 a.m. London time for the second

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[21] We use October 2015 as the starting point of the sample period because our data for the FTSE-100 index futures starting at 1:00 a.m. London time begins at that time.
[22] The results are essentially the same if we use raw returns instead of the VAR residuals.

covariance matrix shift, the *p*-value of the test of overidentifying restrictions is below 5%, indicating that our identification assumptions are rejected. Therefore, we use the two 15-minute intervals immediately before and immediately after 8:15 a.m. London time. Panel A of Figure A1 shows that in the latter interval volatility of the FTSE-100 futures returns declines after a large increase in the previous 15-minute interval. The variances of the E-mini S&P 500 and the Nikkei-225 futures returns also increase substantially and then decline around the opening of the British stock market.

All three markets also show large increases in volatility at the time of release of major U.S. macroeconomic announcements at 8:30 a.m. U.S. ET. On about half of the days in the sample, the FTSE-100 futures did not trade at the time of the Japanese stock market opening due to daylight saving time changes. Therefore, for the third covariance matrix shift we use the two 15-minute intervals immediately before the ending of the Nikkei-225 and TOPIX index futures trading in Japan at 3:15 p.m. Tokyo time.[23] Panel B of Figure A1 shows a substantial increase in volatility of the Nikkei-225 futures returns in the interval from 3:00 p.m. to 3:15 p.m. Tokyo time relative to the immediately preceding 15-minute interval.

Table A1 reports the estimation results. The *p*-value of the test of overidentifying restrictions is about 0.83, showing that our identification assumptions are not rejected by the data. Seven of the nine estimates of the heteroskedasticity parameters are statistically significant. Consistent with Figure A1, six of these estimates, which capture changes in the variance of return innovations around the opening of the U.S. stock market and the closing of index futures trading in Japan, are positive. The remaining three estimates that measure changes in return

[23] The trading hours of the stock and equity index futures markets in Japan are listed at https://www.jpx.co.jp/english/derivatives/rules/trading-hours/. The CME's Nikkei-225 futures that we use continue to trade with much lower volume after 3:15 p.m. Tokyo time.

variance after 8:15 a.m. London time are negative. These estimates confirm that the variances of stock return innovations are higher during periods of elevated trading activity around the market opening and closing times, as more information is impounded into stock and index futures prices through trading (for example, French and Roll, 1986).

The estimated responses of the British and Japanese stock markets to the U.S. market are much larger than the estimates of the response of the U.S. market to these markets. These estimates of the cross-country stock market linkages are both statistically significant and economically meaningful. For example, a 1% increase in the S&P 500 index increases the FTSE-100 index by approximately 0.34%, whereas a 1% increase in the FTSE-100 index increases the S&P 500 index by only about 0.14%. The difference between the two coefficient estimates is statistically significant at the 1% level. The estimates of the effect of the Japanese index futures returns on the U.S. and U.K. stock returns are larger in economic and statistical terms than the estimates of the effect of the FTSE-100 index futures returns on the S&P 500 and Nikkei-225 indices. For example, a 1% increase in the Nikkei-225 index increases the FTSE-100 index by approximately 0.21%, whereas a 1% increase in the FTSE-100 index increases the Nikkei-225 index by only about 0.07%. The response of the U.S. stock market to the Japanese market is more than twice as large as its response to the British market. Overall, these estimates are consistent with the relative sizes of the three stock markets.

It is useful to compare our estimates of international stock market linkages with estimates from other studies using different methodologies. Using identification through heteroskedasticity with daily data from 1989 to 2008, Ehrmann, Fratzscher, and Rigobon (2011) find a response of European stocks to the U.S. stock market that is somewhat larger than our estimate of the response of the British equity market to the U.S. market. However, they find no statistically significant effect of the European stock returns on the U.S. stock market, whereas we show that the U.S. stock market does respond to both British and Japanese stock returns. Using 5-minute index futures data during an economic expansion from July 1998 to February 2001, Andersen et al. (2007) estimate contemporaneous links between international equity markets that are much weaker than our estimates. It is possible that international stock market linkages, particularly the feedback from foreign markets to the U.S. stock market, have strengthened in recent years. This has important implication for investors because it influences benefits of international portfolio diversification.

2. Analysis of contemporaneous links among multiple asset classes

We have shown that the proposed identification based on recurring intraday volatility shifts can be used to examine contemporaneous links among international stock markets. To provide another example, we apply the same methodology to examine contemporaneous effects of multiple asset classes on one another. Henderson, Pearson, and Wang (2015) note a large increase in investor exposure to commodities in recent years. Therefore, in addition to the three financial asset classes (stocks, government bonds and foreign exchange) examined in Andersen et al. (2007), we include crude oil. Specifically, we use the E-mini S&P 500 futures, 30-year U.S. Treasury bond futures, Euro FX futures, and WTI crude oil futures. To simplify interpretation of the results, we express the euro futures exchange rate in dollars per euro.

Our sample period extends from January 2010 through December 2019. We use the most actively traded (usually nearby) contracts for all four futures markets. All four futures contracts are traded on the CME almost 24 hours a day, with a break from 5:00 p.m. to 6:00 p.m. U.S. ET. As before, we use residuals from a VAR that includes the 15-minute returns for the four futures markets during their trading hours. We again use the Schwarz information criterion to find the optimal number of lags in the VAR, which results in one lag. In the analysis that follows, R_{1t}, R_{2t}, R_{3t}, and R_{4t} are the VAR residuals for the E-mini S&P 500, 30-year U.S. Treasury bond, Euro FX, and WTI crude oil futures, respectively.

Since we are now looking at four markets, with one shift in the return covariance matrix we have 16 unknown parameters (12 cross-market response coefficients and four innovation variance changes) and ten moment equations. Each additional shift in the covariance matrix provides ten additional moment equations (four variance changes and six covariance changes of VAR residuals) with only four new parameters (changes in the variances of return innovations). We use four shifts in the covariance matrix (i.e., $S \in \{1, 2, 3, 4\}$) that provide 40 moment equations with 28 unknown parameters (12 market response coefficients and 16 heteroskedasticity parameters). As in the previous example looking at international stock markets, we assume the variance of the common shocks σ_z does not change at the time of the covariance matrix shifts. We estimate the model parameters with GMM and use the test of overidentifying restrictions to test our identification assumptions.

Since FOMC announcements have a substantial impact on return volatility of interest rate futures after 2:00 p.m. ET, we remove FOMC announcement days from the sample. Figure A2 shows variance of the VAR residuals for the four futures markets in the interval from 2:30 a.m. to 4:00 p.m. ET computed across 2,472 days in the sample. For the first covariance matrix shift ($S = 1$), we use the 15-minute intervals immediately before and after the U.S. stock market opening at 9:30 a.m. ET. Open outcry trading in Treasury security futures used to start at 8:20 a.m. ET. These futures contracts now trade only electronically on Globex, but trading activity and volatility pick up considerably after 8:20 a.m. Figure A2 shows that variance of the 30-year Treasury bond futures returns more than doubles from the 15-minute interval that ends at 8:15

a.m. to the next 15-minute interval. Therefore, we use these two intervals for the second covariance matrix shift ($S = 2$).[24] Returns in all four markets become more volatile after 3:00 a.m. ET when European financial markets open. Therefore, we use the two 15-minute intervals immediately before and immediately after 3:00 a.m. ET for the third covariance matrix shift ($S = 3$). Open outcry trading in crude oil futures used to stop at 2:30 p.m., and the daily settlement prices for these contracts are still determined shortly before 2:30 p.m. ET. Figure A2 shows a large spike in volatility of crude oil futures in the intraday interval ending at 2:30 p.m., followed by an even larger decline. Therefore, we use the two 15-minute intervals ending at 2:30 p.m. and 2:45 p.m. to compute the fourth shift in the covariance matrix ($S = 4$) used in the GMM estimation.

Similar to our analysis of international stock market, we construct the moment equations using equation A5, where $\boldsymbol{A}$, $\boldsymbol{C}$, and $\boldsymbol{D_S}$ are now 4×4 matrices. Table A1 reports the GMM estimation results. 11 of the 12 cross-market response coefficients are statistically significant. The response coefficient of the Treasury bond market to the stock market is about -0.21 and its *t*-statistic is about -15. Based on a regression of daily changes in Treasury constant maturity yields on daily Treasury bond futures returns, this estimate means that a 1% increase in the S&P 500 index increases 30-year Treasury yield by about 1.6 basis points. The impact of the Treasury bond market on the stock market is also negative and statistically significant. Interestingly, in Andersen et al. (2007) the corresponding coefficient estimate is positive during an earlier economic expansion and negative in a contraction.

[24] The large spike in the variance of the Treasury bond futures returns in the 15-minute interval ending at 8:45 a.m. is due to major U.S. macroeconomic announcements released at 8:30 a.m. The intraday intervals we use for the second shift in the covariance matrix end right before the release time of these announcements.

The estimate of the response of the U.S. dollar exchange rate against the euro to Treasury bond futures is about −0.24 and is strongly statistically significant. In other words, the dollar appreciates against the euro when the U.S. Treasury yields increase and bond prices fall. The stock market tends to respond positively to increases in oil prices, whereas the Treasury bond prices decline and the U.S. dollar depreciates relative to the euro when oil prices go up. Our estimates of the effect of oil price changes on the equity, Treasury bond and foreign exchange markets are qualitatively similar to those reported by Alquist, Ellwanger, and Jin (2020) for the period from September 2008 to October 2017.[25] A one percent increase in the S&P 500 index increases the crude oil futures prices by about 0.66%. Consistent with Tang and Xiong (2012), this high degree of comovement between stocks and oil prices negatively affects diversification benefits of investing in commodity futures or commodity indices that are dominated by energy commodities.

As expected, appreciation of the U.S. dollar leads to a drop in the crude oil futures prices, expressed in U.S. dollars per barrel. Dollar appreciation also tends to negatively affect U.S. stock prices, perhaps because it reduces dollar revenues of U.S. multinational companies. The response of the bond market to changes in the dollar exchange rate is also fairly substantial (about 0.22) and significant at the 1% level. Ten of the 16 estimates of the heteroskedasticity parameters are statistically significant, with the signs consistent with return volatility shifts observed in Figure A2. Finally, the *p*-value of the test of overidentifying restrictions is about 0.23, indicating that our identification assumptions are not rejected.

[25] Alquist et al. (2020) estimate the response of financial markets to oil price changes using instrumental variables obtained from the surprise components of weekly petroleum inventory announcements.

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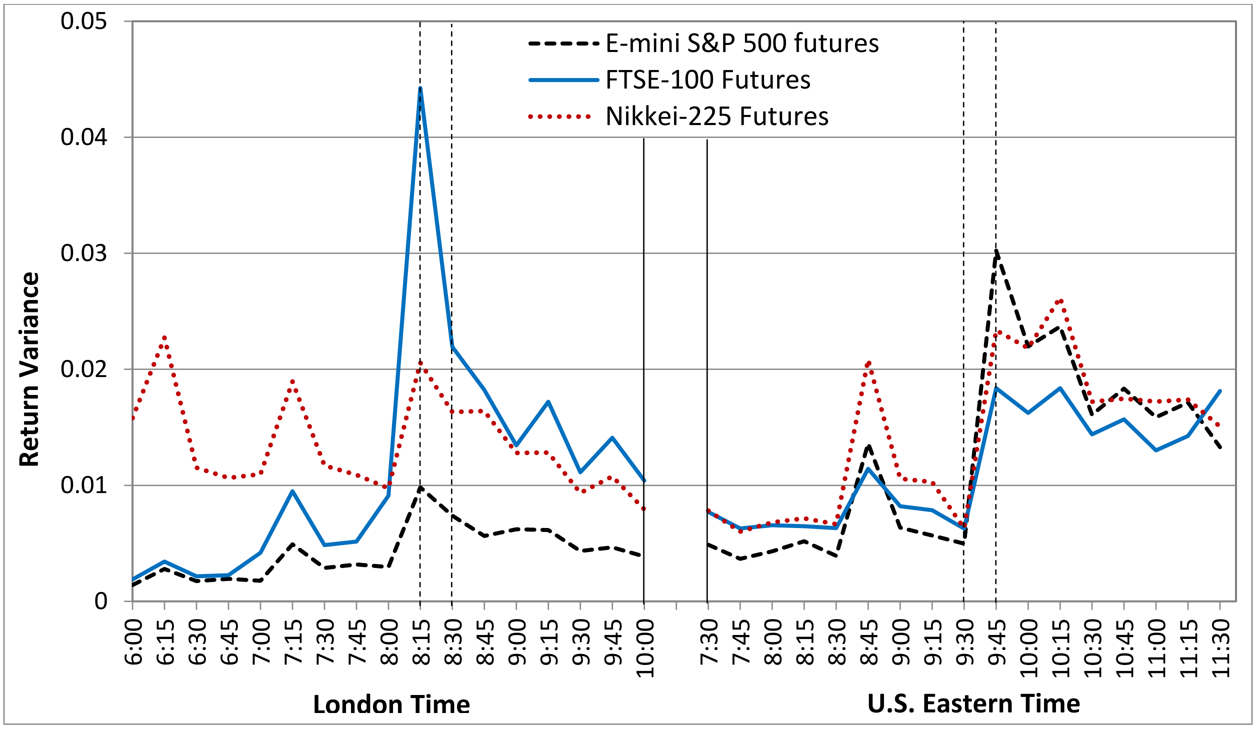
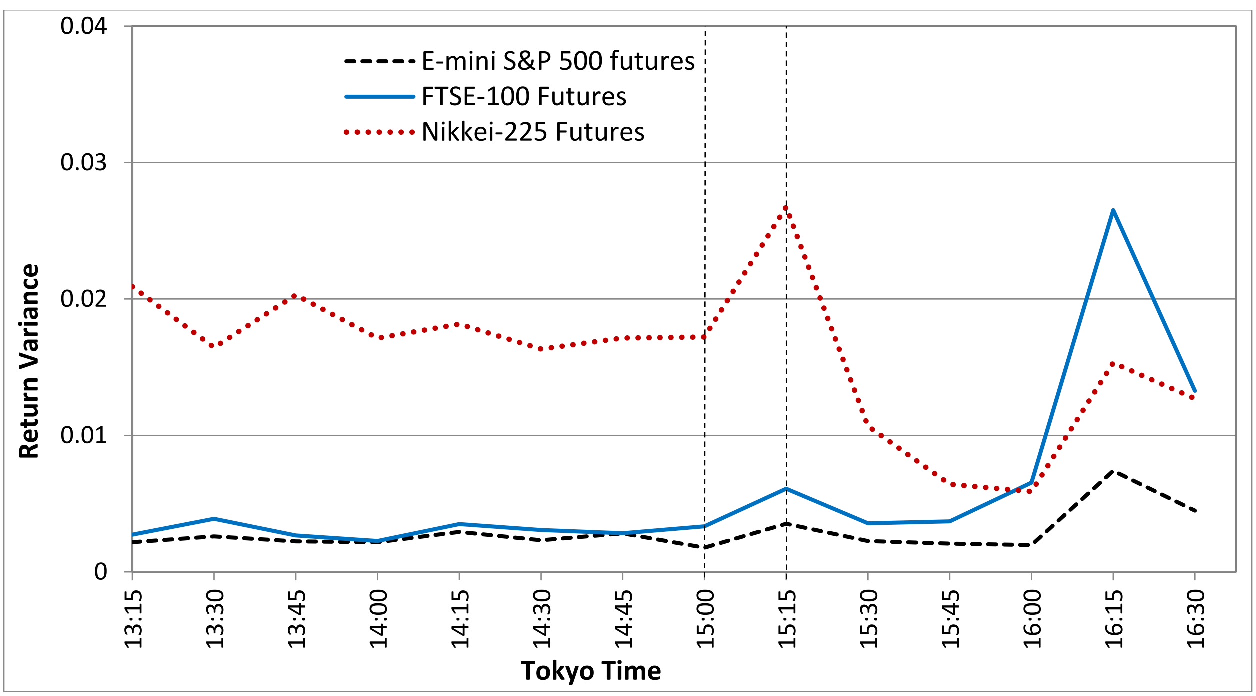
Tang, K., Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, 68, 54-74.

Figure A1
Intraday variation in volatility of international index futures markets

Panel A. Volatility around the opening of the British and U.S. stock markets

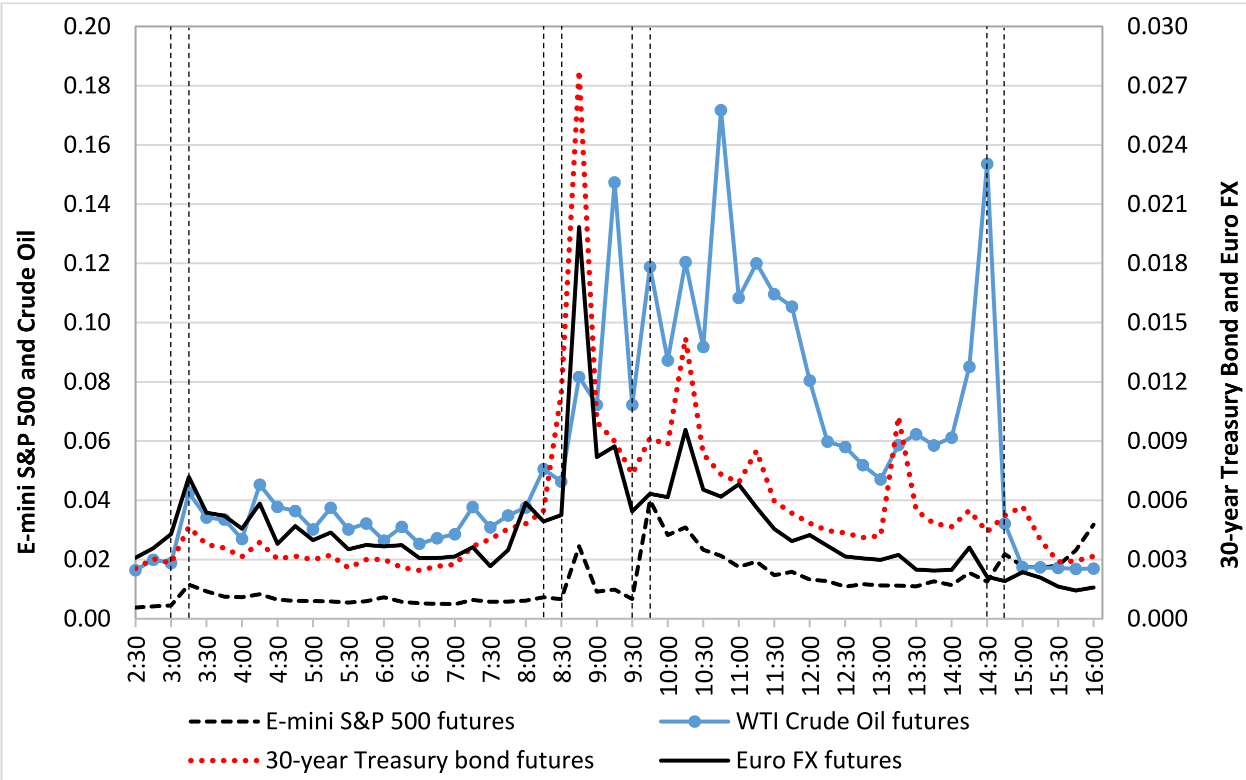


Panel B. Volatility around the close of index futures trading in Japan



The sample period is from October 1, 2015 to December 31, 2019. The variance for each 15-minute interval is computed using residuals from a VAR model of 15-minute futures returns for the E-mini S&P 500, FTSE-100 and Nikkei-225 futures. The vertical dashed lines represent the ending points of the 15-minute intervals used in the GMM estimation.

Figure A2
Intraday variation in volatility of U.S. stock index, Treasury bond, foreign exchange and crude oil futures markets



The sample period is from January 1, 2010 to December 31, 2019. Days of FOMC announcements are omitted from the sample. The variance for each 15-minute interval is computed using residuals from a VAR model of 15-minute returns of the E-mini S&P 500 futures, 30-year U.S. Treasury bond futures, Euro FX futures, and WTI crude oil futures. The vertical dashed lines represent the ending points of the 15-minute intervals used in the GMM estimation.

Table A1
Contemporaneous links between stock index futures markets in the U.S., U.K. and Japan

	Coefficient estimates		Heteroskedasticity parameter estimates
Response of U.S. market to U.K. market (a_{12})	0.1382***	Δ_{11}	0.0122***
	(0.0416)		(0.0020)
Response of U.S. market to Japanese market (a_{13})	0.3155***	Δ_{21}	0.0043***
	(0.0763)		(0.0008)
Response of U.K. market to U.S. market (a_{21})	0.3410***	Δ_{31}	0.0023***
	(0.0603)		(0.0005)
Response of U.K. market to Japanese market (a_{23})	0.2075***	Δ_{12}	-0.0005
	(0.0705)		(0.0003)
Response of Japanese market to U.S. market (a_{31})	0.6756***	Δ_{22}	-0.0169***
	(0.0417)		(0.0022)
Response of Japanese market to U.K. market (a_{32})	0.0715*	Δ_{32}	-0.0017**
	(0.0433)		(0.0008)
		Δ_{13}	0.0003
			(0.0003)
		Δ_{23}	0.0014***
			(0.0003)
		Δ_{33}	0.0047***
			(0.0013)

The sample period is from October 1, 2015 to December 31, 2019 and contains 1,065 observations. Δ_{iS} is the change in the variance of returns of market i around time S. i is 1, 2, and 3 for the E-mini S&P 500 futures, FTSE-100 futures and Nikkei-225 futures, respectively. S is 1, 2, and 3 for the covariance matrix shifts at 9:30 a.m. U.S. ET, 8:15 a.m. London time, and 3:00 p.m. Tokyo time, respectively. The parameters are estimated with GMM. Standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The *p*-value of the test of overidentifying restrictions is 0.8288.

Table A2
Contemporaneous links between stock index, Treasury bond, foreign exchange (FX) and crude oil futures returns

	Coefficient estimates		Heteroskedasticity parameter estimates
Response of stock market to Treasury bond market (a_{12})	-0.0852**	Δ_{11}	0.0277***
	(0.0388)		(0.0020)
Response of stock market to FX market (a_{13})	-0.1985**	Δ_{21}	0.0004
	(0.0966)		(0.0004)
Response of stock market to crude oil market (a_{14})	0.0585***	Δ_{31}	0.0008**
	(0.0093)		(0.0004)
Response of Treasury bond market to stock market (a_{21})	-0.2087***	Δ_{41}	0.0313***
	(0.0144)		(0.0088)
Response of Treasury bond market to FX market (a_{23})	0.2234***	Δ_{12}	0.0003
	(0.0752)		(0.0005)
Response of Treasury bond market to crude oil market (a_{24})	-0.0096**	Δ_{22}	0.0066***
	(0.0046)		(0.0008)
Response of FX market to stock market (a_{31})	-0.0845***	Δ_{32}	0.0004
	(0.0191)		(0.0005)
Response of FX market to Treasury bond market (a_{32})	-0.2354***	Δ_{42}	-0.0040
	(0.0394)		(0.0031)
Response of FX market to crude oil market (a_{34})	-0.0135***	Δ_{13}	0.0056***
	(0.0036)		(0.0005)
Response of crude oil market to stock market (a_{41})	0.6583***	Δ_{23}	0.0012***
	(0.0537)		(0.0002)
Response of crude oil market to Treasury bond market (a_{42})	0.0903	Δ_{33}	0.0030***
	(0.0878)		(0.0004)
Response of crude oil market to FX market (a_{43})	-0.3586**	Δ_{43}	0.0175***
	(0.1546)		(0.0024)
		Δ_{14}	0.0023
			(0.0019)
		Δ_{24}	-0.0001
			(0.0002)
		Δ_{34}	-0.0002*
			(0.0001)
		Δ_{44}	-0.1160***
			(0.0091)

The sample period is from January 1, 2010 to December 31, 2019 and contains 2,472 observations. Days of FOMC announcements are omitted from the sample. Δ_{iS} is the change in the variance of returns of market i around time S. i is 1, 2, 3, and 4 for the E-mini S&P 500 futures, 30-year U.S. Treasury bond futures, Euro FX futures and WTI crude oil futures, respectively. S is 1, 2, 3, and 4 for the covariance matrix shifts at 9:30 a.m., 8:15 a.m., 3:00 a.m., and 2:30 p.m. U.S. ET, respectively. The parameters are estimated with GMM. Standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The *p*-value of the test of overidentifying restrictions is 0.2328.