The Response of Stock Market Volatility to Futures-Based Measures of Monetary Policy Shocks

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ABSTRACT

In this paper, we investigate the dynamic response of stock market volatility to changes in monetary policy. Using a vector autoregressive model, our findings reveal a significant and asymmetric response of stock returns and volatility to monetary policy shocks as well as an economically important reaction of the variance risk premium to monetary policy. The short-term increase in futures-trading volume and leverage appear to have a limited effect on volatility. The longer-term dynamics of volatility is dominated by monetary policy’s effect on fundamentals. Furthermore, the estimation results from a bivariate GARCH model tend to suggest a novel and significant bidirectional volatility relationship between the stock and federal funds futures markets.

KEYWORDS: Stock market volatility, Federal funds futures, monetary policy, variance risk premium, vector autoregression, bivariate GARCH, leverage effect, volatility feedback effect

JEL codes: C32, C58, E52, E58, G10, G12

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1. Introduction

The effect of Federal Reserve (Fed) actions on the stock market has garnered substantial policy-making, practical and research interest. A change in the federal funds rate, the Fed’s policy instrument, is closely associated with changes in various short-term interest rates. This, in turn, influences the discount rate used to value the cash flows from equities (i.e. dividends). Monetary policy also affects the stock market through its effect on financial leverage: each rate change by the Fed changes the cost for firms to finance their activities through issuing debt.¹

While the extant literature (Bernanke and Kuttner, 2005; Goto and Valkanov, 2002; Thorbecke, 1997 and Patelis, 1997) widely documents a decrease in stock market returns following a monetary policy tightening, the effect of Fed actions on stock market volatility are less documented and understood. Nevertheless, the response of the stock market to Fed actions need not be limited to returns and can extend to stock price volatility through a number of channels.

On the one hand, as first documented in Black (1976) and Christie’s (1982) seminal contributions, an asymmetric relationship exists between stock returns and volatility. Black (1976) and Christie (1982) attribute the increase in volatility to a higher leverage (debt-to-equity) ratio and researchers since refer to the asymmetric return-volatility relationship as the leverage effect. In view of the established decrease in stock prices following a monetary policy tightening, an increase in volatility can thus result from the leverage channel.

On the other hand, monetary policy can exert a direct influence on risk premiums and volatility. In fact, an alternative view of the asymmetric return-volatility relationship proposed by Campbell and Hentschel (1992) and subsequently referred to as the volatility feedback
hypothesis, postulates that negative news spur an increase in future volatility. According to the volatility feedback hypothesis, time-varying risk premiums relate the increase in future volatility to a decrease in contemporaneous returns. More specifically, the negative news leads to an increase in the expected stock returns (i.e. risk premiums) as investors require additional compensation to account for the increased riskiness of holding stocks. If volatility is a priced risk factor, and given a positive correlation between future volatility and expected returns, the increase in future volatility feeds back into and lowers contemporaneous returns. In sum, negative news decreases returns contemporaneously and increases both future volatility and expected stock returns. An unexpected monetary policy tightening constitutes negative news to stocks whose future cash flows (dividends) are valued at a higher than expected discount rate. This implies that a monetary policy shock is expected to decrease returns contemporaneously and to increase future stock market volatility. Evidently, both the leverage and volatility feedback channels can operate simultaneously as argued in Wu (2001).

An unexpected monetary policy tightening, which represents new information to investors, can also increase volatility through its effect on trading activity. In light of the new information available in the market, investors may rebalance their portfolios more intensively between equities and bonds thus spurring an increase in trading volume. The increase in trading volume could, in turn, translate into higher volatility due to the well-known positive relation between volatility and trading volume (Karpoff, 1987; Andersen, 1996, among others). Such an increase in volatility would also be in line with Ross’s (1989) analysis suggesting that information flow into the market positively correlates with volatility.
While previous research (Lobo, 2000; Bomfim, 2003; Flannery and Protopapadakis, 2002) uses Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to investigate the link between monetary policy and the volatility of some assets, the existing literature did not assess the *dynamic* effect of monetary policy shocks on stock market volatility (variance risk premium) nor investigate the channels through which monetary policy affects volatility. In an influential contribution, Schwert (1989) studies the relationship between macroeconomic and stock market volatility but does not explicitly tackle the effect of monetary policy on stock market volatility.

In this paper, we undertake an in-depth analysis, at the monthly level, of the effect of futures-based monetary policy shocks on stock market volatility and the variance risk premium. We examine the dynamic effects of monetary policy shocks, identified from Federal funds futures data, by employing a vector autoregressive (VAR) model. The use of market-based measures of monetary policy shocks allows us to avoid the need to resort to identifying assumptions and circumvents dimensionality (degrees of freedom) problems in the estimated VAR. Our goal from this analysis is threefold. First, we assess the dynamic response of stock market volatility and the variance risk premium to monetary policy shocks. Second, our analysis allows us to characterize asymmetries in the return-volatility relationship. Third, we study the channels through which monetary policy shocks affect stock market volatility by analyzing the joint response of several financial variables to market-based measures of monetary policy shocks. By inspecting the channels of monetary policy transmission to volatility, we also identify the importance of changes in the risk premium or leverage on stock market volatility and,
therefore investigate in further detail the importance of the volatility feedback and leverage effect hypotheses.

Our results show a contemporaneous decrease in excess returns of 1% and an increase in stock market volatility which peaks one month following the shock at 0.8%. The results illustrate an asymmetric return-volatility relationship and demonstrate that monetary policy exerts an effect on the variance risk premium. We further explore the effect of monetary policy by estimating a bivariate GARCH model relating federal funds futures to stock market volatility. The bivariate GARCH model uncovers a novel and significant bidirectional volatility effect.

To the best of our knowledge, this study is the first to examine the dynamic response of stock market volatility (variance risk premium) to monetary policy shocks and to examine the transmission of monetary policy to volatility. Such an exploration would be of central importance from a theoretical and practical perspective. Theoretically, volatility is a key component of many derivative pricing models and an understanding of the dynamic response of volatility to monetary policy shocks would allow for better derivative pricing. From a practical perspective, the advent of derivatives on market volatility and their increasing popularity with investors shows that volatility, while itself not being a tradable asset, is an underlying asset for a number of derivatives contracts. In addition, a more complete understanding of the role of monetary policy in affecting the variance risk premium would contribute to a better understanding of risk taking behavior in financial markets, as discussed in further detail in Section 3.2.
The plan of the paper is as follows: Section 2 discusses the data and variables we employ, Section 3 presents the econometric methodology and results while Section 4 offers some concluding remarks.

2. Data and Variable Description

2.1 Stock index returns, stock market volatility and the volatility risk premium

Daily and monthly closing price data on the Standard and Poor’s S&P500 index are obtained from Yahoo! Finance. Let $P_{n,t}$ denote the closing index price on day $n$ of month $t$. Continuously compounded daily returns are computed as:

$$R_{n,t} = \ln(P_{n,t}) - \ln(P_{n-1,t}).$$

(1)

We also compute the monthly excess returns on the S&P500 index by subtracting the three month T-bill rate (considered as a proxy for the risk-free rate) from the monthly returns on the S&P500:

$$ER_t = R_t - TB_t.$$  

(2)

Monthly realized stock market volatility is computed, in turn, from daily squared returns as in Bandi and Perron (2006):

$$VOL_t = 252 \times \sqrt{\frac{1}{N}\sum_{n=1}^{N} R_{n,t}^2},$$

(3)

where $N$ denotes the number of trading days in month $t$.

Following Zhou (2010) we define the variance risk premium (VRP) as the difference the risk-neutral and statistical expectations of the return variance. While the ex-ante risk neutral expectation is measured using the Chicago Board of Options Exchange (CBOE)’s implied
volatility (VIX) index, a linear regression with one lag of implied and realized variance is employed to obtain the statistical expectation of the realized variance.

In addition to excess returns and volatility, we employ the following variables in the VAR model: the real interest rate ($RINT$) defined as the difference between the three month T-bill rate and the consumer price inflation, the change in the three month T-bill rate ($DTB$), the dividend yield on the S&P500 ($DY$), the change in the S&P 500 futures trading volume ($VOLUME$) and financial leverage ($LEVERAGE$) as proxied by the monthly growth in commercial and industrial loans made by all commercial banks.

Table 1 reports the summary statistics of the variables employed in the empirical analysis.

[Insert Table I here]

The results in Table 1 indicate that the dividend yield exhibits very high persistence that is well documented in the literature. Table 1 also shows that the variance risk premium is, on average, positive and despite the strong persistence in realized and implied volatilities, it exhibits only weak serial correlation.

2.2 Federal funds futures

Federal funds futures, officially known as 30-day interest rate futures, are interest rate futures that settle on the average of the month’s overnight funds rate. These futures contracts started trading on the Chicago Board of Trade (CBOT) in 1988 and contracts ranging from the current (spot) month to several months ahead exist. Krueger and Kuttner (1996), Gurkaynak, Sack and Swanson (2007) and Hamilton (2009) provide empirical evidence supporting the efficiency of
the federal funds futures market. Given the evidence in favor of the efficiency of federal funds futures, several studies have proposed extracting monthly and daily measures of monetary policy shocks from these contracts.

Following Bernanke and Kuttner (2005), a monthly monetary policy shocks series is computed from futures prices. Let $FF_{n,t}^i$ denote the one-month-ahead implied rate for day $n$ of month $t$, and $FFTR_{n,t}$ denote the Federal funds target rate for day $n$ in month $t$, the monthly monetary policy shock is given by:

$$MP_t = \frac{1}{N} \sum_{n=1}^{N} FFTR_{n,t} - FF_{N,t-1}^i,$$

where $FF_{N,t-1}^i$ denotes the one-month-ahead futures rate on the last ($N^{th}$) day of month $t-1$.

In addition, we use daily changes in federal funds futures rates to gauge changes in monetary policy expectations. Hamilton (2009) maintains that daily changes federal funds futures rates are indicative of market participants’ expectations of the future level of the federal funds rate. This, in turn, implies that daily changes in federal funds futures contracts signal market participants’ changing expectations about the future course of monetary policy and can be used as a direct gauge of monetary policy expectations. Following Hamilton (2009), we use daily changes in the implied rates, $\Delta FF_{n,t}^i = FF_{n,t}^i - FF_{n-1,t}^i$, to measure changes in market participants’ expectations of the future course of monetary policy.
3. Econometric Methodology and Results

3.1 Structural Vector Autoregressions (SVARs)

Let \( Y_t \) denote an \((K \times 1)\) vector of macroeconomic and financial time series of interest and \( X_t \) be an \((M \times 1)\) vector of exogenous variables. A \( p^{th} \)-order structural vector autoregressive [SVAR\((p,q)\)] is given by

\[
B(L)Y_t = \Gamma(L)X_t + \epsilon_t,
\]

where \( B(L) = B_0 - B_1L - B_2L^2 - \cdots - B_pL^p \) is a matrix lag polynomial of order \( p \) whose roots lie strictly outside the unit circle, \( \Gamma(L) = \Gamma_0 + \Gamma_1L + \Gamma_2L^2 + \cdots + \Gamma_qL^q \) is a matrix lag polynomial of order \( q \) and the \((K \times 1)\) vector \( \epsilon_t \) denotes the structural innovations (shocks) that the researcher seeks to identify.

Imposing identifying assumptions on the contemporaneous impact matrix \( B_0 \) has been common in the literature (Bernanke, 1986; Sims, 1980). In the context of identifying monetary policy shocks, the most common (though by no means the only) identification strategy imposes a recursive (or Wold recursive) assumption on a model such as equation (5) (Boivin and Giannoni, 2002; Christiano, Eichenbaum and Evans, 1999; Goto and Valkanov, 2002; Thorbecke, 1997). While a recursive identification assumption allows for a response of the stock market to monetary policy shocks, it precludes a direct response of the Fed to the stock market. A simultaneous response by the Fed to the stock market, as documented in some recent studies (Rigobon and Sack, 2003), would create endogeneity and invalidate an identification scheme based on a recursive identification. Recent studies pursue identification strategies that make use of futures data (Faust, Swanson and Wright, 2004) or identify monetary policy shocks based on...
conditional heteroskedasticity (Rigobon and Sack, 2003). In this paper, we follow Bernanke and Kuttner (2005) and circumvent identification problems by employing market-based measures of monetary policy shocks obtained from Federal funds futures data.

The impulse response to a one standard deviation monetary policy shock can be obtained from the infinite order vector moving average representation of the finite order SVARX(p,q) model in equation (5). The 95% confidence bands are computed using the Monte Carlo method of Sims and Zha (1999).

3.2 The VAR model

In this section, we present the VAR model employed and study the channels of transmission of monetary policy shocks to volatility. Campbell and Ammer (1993) provide a decomposition of returns in terms of news regarding dividends and expected returns. Patelis (1997) and Bernanke and Kuttner (2005) further extend the decomposition to include the real interest rate. Let $tER$ denote excess returns at time $t$. Then, following Bernanke and Kuttner (2005) excess returns can be written as:

$$ER_t - E_t(ER_{t+1}) = (E_{t+1} - E_t) \left\{ \sum_{j=0}^{\infty} \rho^j \Delta D_t + \sum_{j=1}^{\infty} \rho^j RINT_t - \sum_{j=1}^{\infty} \rho^j ER_{t+1} \right\},$$

(6)

where $E_t$ denotes the conditional expectation operator (given the information set at time $t$), $D_t$ denotes the log dividend at time $t$, $RINT_t$ denotes the real interest rate at time $t$ and $\rho$ is a constant (generally set close to one) which equals the ratio of ex-dividends to the cum-dividends.

As convincingly argued in Patelis (1997) and Bernanke and Kuttner (2005), the decomposition in equation (6) illustrates the various channels through which monetary policy
can affect returns. Contractionary monetary policy can exert an effect on stock market returns by
decreasing expected future dividends, increasing the expected excess returns or increasing the
future expected real interest rate used to discount dividends. As argued earlier, monetary policy’s
effect can extend to volatility through a multitude of channels: its effect on time-varying risk
premiums (volatility feedback hypothesis), on financial leverage (leverage effect) or on discount
rates and trading activity.

In order to simultaneously examine the response of stock market volatility, returns and
the transmission of monetary policy to volatility, the variables included in equation (6) are
incorporated into our VAR. Following Bernanke and Kuttner (2005), we employ the following
VAR model to assess the effect of monetary policy shocks (\( MP \)), computed from equation (4),
on financial variables:

\[
Y_t = A_t Y_{t-1} + \Phi_0 MP_t + \omega_t, \tag{7}
\]

where \( Y_t = [ER \ VOL \ VRP \ RINT \ DTB \ DY \ LEVERAGE \ VOLUME]^T \). In addition to excess
returns, volatility, the variance risk premium, the real interest rate, the change in the T-bill rate
and the dividend yield, we include in the VAR a measure of financial leverage and the change in
of a positive correlation between unexpected futures-trading volume and volatility. Following
Bessembinder and Seguin (1993), we consider the residuals from a AR(10) model of the change
in log volume to be the unexpected component of S&P 500 futures volume.\(^7\) In equation (7), \( \Phi_0 \)
summarizes the contemporaneous response of \( Y_t \) to an exogenous monetary policy shock. In
comparison to equation (5), the lag polynomial matrices \( B(L) \) and \( \Gamma(L) \) specialize to the
matrices \( A_t \) and \( \Phi_0 \).
There are a number of advantages that stem from using the VAR model in equation (7) in comparison to using a conventional monetary VAR in which several macroeconomic variables need to be incorporated in order to properly identify monetary policy shocks. First, the financial variables of interest cannot be included in a typical monetary VAR as this would entail estimating a large number of parameters and leads to degrees of freedom problems. Embedding the monetary policy shocks as an exogenous variable in the VAR thus circumvents the need to estimate a large VAR model in order to properly identify the monetary policy shocks. Second, the VAR model in equation (7) allows for analyzing the joint dynamics of several financial variables to a monetary policy shock. This desirable feature of the model allows for a closer inspection of the channels through which monetary policy shocks affect the stock market.

The effect of the monetary policy shock at time $t$ on $Y_{t+j}$ is measured by $A_t'\Phi_0$. The standard errors and confidence bands for the estimated responses can be constructed using the delta method (Lutkepohl, 2006). Instead, we follow Basu, Fernald and Kimball (2006) and compute the 95% confidence bands from a near-VAR by using the Monte Carlo method of Sims and Zha (1999). The response of the financial variables to a one standard deviation (10 basis points increase) contractionary monetary policy ($MP$) shock, for a horizon of twelve months, is displayed in Figure 1.

[Insert Figure 1 here]

The impulse responses in Figure 1 show that a one standard deviation contractionary shock leads to a contemporaneous decrease of one percentage point in excess returns. The well established (Thorbecke, 1997; Bernanke and Kuttner, 2005) initial decrease in excess returns is short-lived and lasts for around one month.
While the response of returns is in line with results reported in prior studies, a number of interesting and novel observations emerge from the dynamic response of volatility to a monetary policy shock. First, an MP shock leads to a contemporaneous increase in volatility of around 0.3%. The increase in volatility peaks at around 0.8% one month after the shock. The response of volatility reverts back to 0.4% after its peak and is persistently positive twelve months after the shock. Second, the joint responses of excess returns and volatility are suggestive of an asymmetric lead-lag relationship in which excess returns decrease contemporaneously due to an MP shock, while volatility’s response is most pronounced one month after the shock. This finding confirms the widely documented (Black, 1976; Christie, 1982; Campbell and Hentschel, 1992) asymmetric response of volatility to past return shocks.

The asymmetric response of volatility and excess returns to a monetary policy shock conforms to economic intuition. As argued before, a monetary policy shock can affect returns and volatility through its effect on discount rates, risk premiums, financial leverage or trading activity. Regardless of the exact channel through which Fed actions operate, we argue that a monetary policy tightening constitutes negative news to stocks. The negative news translates into an increase in future volatility (and expected returns) and a contemporaneous decrease in excess returns. The impulse responses in Figure 1 illustrate the asymmetry between the returns and volatility and are consistent with both the leverage effect of Black (1976) and Christie (1982) and the volatility feedback effect of Campbell and Hentschel (1992).

While both the leverage effect and volatility feedback hypothesis imply an asymmetric return-volatility response, we note that the causality implications of the two hypotheses are different. In fact, the leverage effect hypothesis stipulates that future volatility increases because
of the contemporaneous decrease in stock prices (and the resulting increase in the debt-to-equity ratio) whereas the volatility feedback hypothesis postulates that the increase future volatility drives the decrease in contemporaneous stock returns. Therefore, as argued in Wu (2001) and Bekaert and Wu (2000), the causality implications of the two hypotheses are different. Causality runs from stock returns to volatility under the leverage effect hypothesis whereas the volatility feedback hypothesis implies that the increase in volatility causes stock returns to decrease contemporaneously. A closer inspection of the dynamic response of financial leverage and the variance risk premium to an MP shock, as discussed next, can assist in determining the importance of the leverage and risk aversion channels in the transmission of MP shocks to volatility.

Given that the volatility feedback hypothesis attributes the response of volatility to changes in risk premiums, we turn to a more extensive analysis of the effect of monetary policy changes on risk premiums. Our analysis centers on the variance risk premium, in particular, because a number of studies provide empirical evidence of a positive correlation between market-wide risk aversion and the variance risk premium (Rosenberg and Engle, 2002; Bollerslev, Tauchen and Zhou, 2009; Bollerslev, Gibson and Zhou, 2011).9

Figure 1 shows a contemporaneous increase in the variance risk premium by 1.5% following the MP shock. The variance risk premium remains persistently positive twelve months following the monetary policy shock, although its response becomes less pronounced and stabilizes at around 0.5% one month following the monetary policy shock. We note that while the response of volatility peaks one month following the shock, the response of the variance risk premium is most pronounced contemporaneously. This, in turn, is suggestive of a lead-lag
relationship between the variance risk premium and volatility. Due to the positive correlation
between the variance risk premium and market-wide risk aversion, our results suggest that
contractionary monetary policy increases market-wide risk aversion. The impulse response
analysis lends support to the volatility feedback hypothesis according to which changes in risk
premiums drive changes in volatility.

The leverage effect hypothesis posits that changes in volatility are driven by changes in
leverage. The VAR model in equation (7) therefore comprises a measure of financial leverage
and Figure 1 also lends empirical support to the presumption that monetary policy shocks
transmit to volatility through the leverage channel. As expected, the increase in interest rates
following the monetary policy shock also increases leverage due to the increase in the cost of
issuing debt. The slow mean reverting increase in leverage, in turn, corresponds with an increase
in stock market volatility. Our findings thus far seem to point to the fact that both the leverage
and risk premiums channels contribute to changes in volatility.

The change in the T-bill rate exhibits a contemporaneous and positive response to a
futures-based monetary policy shock. The response of the change in the T-bill rate reverts back
to zero around six months following the shock. The dynamics of the real interest rate show an
initial contemporaneous decrease. The real interest rate then turns and remains persistently
positive five months after the shock. The decrease in the real interest rate indicates that,
following the monetary policy shock, inflation increases proportionately more than the nominal
interest rate. The decrease in the real interest rate likely reflects the presence of a price puzzle in
the VAR. Taken together, the responses of the interest rate variables are suggestive of an
important response of short-term interest rates, and by extension, of discount rates, to monetary policy shocks.

The unexpected S&P 500 futures-trading volume also increases contemporaneously due to the monetary policy shock. The increase in trading volume is short-lived and lasts for two months following which trading volume becomes slightly negative before reverting back to zero seven months after the MP shock. It is interesting to note that the increase in volatility corresponds to an increase in S&P futures-trading and that volatility decreases when trading volume becomes negative. The positive relationship between futures-trading activity and volatility is consistent with Bessembinder and Seguin (1993) and with the notion that the monetary policy shocks constitute new information arrival into the market that drives investors to rebalance their portfolios more intensively.

Finally, the dividend yield also strongly responds to a monetary policy shock. Due to the decrease in stock prices, the dividend yield shows a persistent increase. In sum, the impulse responses in Figure 1 uncover that the discount (interest) rate, leverage, risk premium, trading volume and dividend channels all contribute to the increase in volatility. In order to better assess the importance of each of the channels, Table 2 provides the forecast error variance decompositions, for a horizon of twelve months, from the VARX(p,q) in equation (7).

[Insert Table II here]

The variance decompositions in Table 2 show that a monetary policy shock accounts for 5.79% and 3.37% of the variance of excess returns and volatility, respectively. A monetary policy innovation accounts for a modest 1.25% of the variance of the risk premium, while accounting for a larger proportion (4.62%) of the variance of leverage. Whereas an MP shock
accounts only for a small proportion of the variances futures-trading volume (1.65%) its effect on the change in the T-bill rate (12.33%) and the dividend yield (18.66%) are more sizeable.

The variance decomposition of stock market volatility shows that, aside from shocks to volatility itself and to returns, a monetary policy innovation accounts for the biggest proportion of the variance of volatility. Innovations to financial leverage amount only to 0.48% of the variance of volatility. While our findings document an direct role of monetary policy in affecting stock returns, volatility and (to a lesser extent) the variance risk premium, they cast doubt on ascribing the bulk of stock market variables responses’ to financial leverage or trading volume. In fact, the variance decompositions indicate that, aside from an own shock to excess returns, volatility or the variance risk premium, the largest proportion of the variance in these variable is due to innovations in returns.

It is interesting to note that, in comparison with the smaller proportion of the variance of financial leverage explained by monetary policy innovations, the largest proportion of the variance in the dividend yield (aside from own and return innovations) and the change in the T-bill rate is explained by monetary policy innovations. This, in turn, suggests that once the effect of an MP shock on interest rates and trading volume dies out, the dynamics of excess and volatility are dominated by the persistent effect that monetary policy exerts on fundamentals (the dividend yield).

3.3 Federal funds futures and stock market volatility

In view of the response of stock market volatility to monetary policy uncovered in the prior section, we turn next to investigating the relationship among the stock market and monetary
policy expectations, gauged using futures data, at the daily level. Specifically, we examine the volatility interaction among the stock and federal funds futures markets. To do so, we use daily continuously compounded returns on the S&P 500 (in percent) as well as the daily changes in the implied interest rates from federal funds futures (in basis points) for the period January 1990 to December 2007.

Hamilton (2009) maintains that daily changes in federal funds futures rates provide a direct measure of changes in market expectations of monetary policy actions. Using daily changes in futures rates would thus allow for investigating volatility relationships between monetary policy and the stock market. Hamilton (2009) also provides evidence that the daily changes in federal funds futures rates exhibit strong conditional heteroskedasticity. We conduct tests for ARCH effects for S&P 500 returns and the daily changes in federal funds futures rates and our results (not reported) indicate strong conditional heteroskedasticity in all the series.

Given the conditional heteroskedasticity present in the daily changes in federal funds futures rates, we proceed with jointly modeling the stock and federal funds futures volatility using a bivariate GARCH model. Unlike the VAR models considered previously, the models entertained in this section make use of daily data and of information beyond the one-month-ahead futures contracts. Furthermore, they do not address the effect of a monetary policy shocks on stock market volatility per se, but rather the volatility interaction among market expectations of monetary policy and the stock market. We treat stock market volatility as a latent process and employ the following constant correlation bivariate GARCH model proposed by Ling and McAleer (2003):

\[
\begin{bmatrix}
R_t \\
\Delta FFFF_T^{-1}
\end{bmatrix} = 
\begin{bmatrix}
\mu_R \\
\mu_F
\end{bmatrix} + 
\begin{bmatrix}
\varepsilon_{R,t} \\
\varepsilon_{F,t}
\end{bmatrix}
\]

(8)
\[
\begin{bmatrix}
\varepsilon_{R,j} \\
\varepsilon_{F,j}
\end{bmatrix} =
\begin{bmatrix}
\eta_{R,j} \\
\eta_{F,j}
\end{bmatrix}
\begin{bmatrix}
\eta_{R,j} \\
\eta_{F,j}
\end{bmatrix}
\begin{bmatrix}
h_{R,j}^{1/2} & 0 \\
0 & h_{F,j}^{1/2}
\end{bmatrix}
\]

(9)

\[
\begin{bmatrix}
h_{R,j} \\
h_{F,j}
\end{bmatrix} =
\begin{bmatrix}
\omega_R \\
\omega_F
\end{bmatrix} +
\begin{bmatrix}
\alpha_{RR} & \alpha_{RF} \\
\alpha_{FR} & \alpha_{FF}
\end{bmatrix}
\begin{bmatrix}
\varepsilon_{R,j-1}^2 \\
\varepsilon_{F,j-1}^2
\end{bmatrix} +
\begin{bmatrix}
\beta_{RR} & \beta_{RF} \\
\beta_{FR} & \beta_{FF}
\end{bmatrix}
\begin{bmatrix}
h_{R,j-1} \\
h_{F,j-1}
\end{bmatrix},
\]

(10)

where \( \eta_{R,j} \) and \( \eta_{F,j} \) are independently and identically distributed (iid) random variables with mean zero and variance one, \( R_t \) denotes continuously compounded returns on the S&P 500 index computed from daily data, \( \Delta FF_{t} \) denotes the daily changes in the implied interest rates from the one-month-ahead federal funds futures contracts and \( h_{R,j} \) and \( h_{F,j} \) denote the conditional volatilities of stock returns and federal funds futures, respectively.\(^{10}\) Ling and McAleer’s (2003) multivariate GARCH model allows for volatility interdependence across different markets as it models one return’s volatility as dependent on its own lag, the lagged volatilities of the other variables in the system as well as the lagged squared residuals of all the variables included in the system. In the above bivariate GARCH model, \( \alpha_{RF} \) and \( \alpha_{FR} \) measure the effect of cross squared residuals on volatility whereas \( \beta_{RF} \) and \( \beta_{FR} \) measure the cross-market volatility effect. For instance, determining whether federal funds futures volatility affects stock market volatility would entail assessing the significance of the parameters \( \alpha_{RF} \) and \( \beta_{RF} \).

The results from estimating the bivariate GARCH model in equations (8), (9) and (10) are reported in Table 3.

[Insert Table III here]

In line with Hamilton (2009), the results indicate strong GARCH effects in the daily changes in federal funds futures as evinced by the large and significant \( \beta_{FF} \) coefficient on lagged federal
funds futures volatility. Both cross volatility coefficients, $\beta_{RF}$ and $\beta_{FR}$, are highly significant and point to a bidirectional relationship between stock market and federal funds futures volatility. The estimate of $\beta_{RF}$ suggests that an increase in the volatility of the federal funds futures tends to decrease stock market volatility. This is expected because actions taken by the Fed that aim to maintain price stability and economic growth tend to calm down stock markets. Moreover, the estimate of $\beta_{FR}$ indicates that higher stock market volatility decreases the volatility of the futures rates.

The results point to two effects. First, the volatility of federal funds futures contracts possesses predictive power for stock return volatility. Since federal funds futures rates summarize all market participants’ expectations of the future course of monetary policy actions, our results imply a significant role for the uncertainty about the future course of monetary policy in affecting stock market volatility. Our results also suggest that stock market volatility possesses predictive power for federal funds futures volatility. This, in turn, implies that futures markets participants view stock market volatility as an important factor in determining the future monetary policy rate. Such a finding is in agreement with Rigobon and Sack (2003) who use a volatility-based identification scheme for monetary policy shocks.

4. Conclusion

This paper studies the dynamic response of stock market volatility to monetary policy. Using a VAR model that incorporates a futures-based measure of monetary policy shocks, our findings uncover a significant response of stock market volatility to monetary policy shocks. Our results show an asymmetric return-volatility response to a monetary policy shock and reveal an
important response of the variance risk premium, and by extension, of risk aversion, to monetary policy. We also study the channels through which monetary policy affects stock market volatility. Our findings suggest that while leverage and futures-trading volume display an increase following a monetary policy shock, the importance of these channels in affecting short-term changes in volatility is limited. The longer-term dynamic response of volatility appears to be dominated by the persistent effect of monetary policy on stock market fundamentals (dividends). In light of the important dynamic response of stock market volatility to monetary policy, we investigate the volatility interaction among a futures contract written on the monetary policy rate set by the Fed, namely federal funds futures, and the stock market using a bivariate GARCH model. Our analysis points to a bidirectional volatility relationship between the federal funds futures and stock markets. This, in turn, suggests an important role for market participants’ uncertainty about the future course of monetary policy in determining stock market volatility.

Our results entail important practical and policy making implications. From a policy perspective, our results demonstrate that Fed actions have a significant effect on stock market volatility and the variance risk premium. This, in turn, implies that the Fed might be able to influence market volatility and market-wide risk aversion through better communication or increased transparency. From a trading perspective, our results show that investors might be able to trade profitably, by entering into suitable derivatives positions, due to the persistent increase in volatility that follows a monetary policy shock. It would be interesting to explore whether investors can realize a profit, once trading costs are accounted for, using swap contracts.
NOTES

1. Researchers refer to the first channel as the “wealth channel” while the second channel is labeled the “balance sheet” channel. For a survey of the empirical and theoretical research on the relationship between the stock market and monetary policy, see Sellin (2001).

2. Such as the Chicago Board of Options Exchange (CBOE)’s futures and options on the VIX index which began trading in 2004 and 2006, respectively. In addition, variance swaps currently have a liquid market. Carr and Wu (2006) discuss variance swap contracts and the return that accrues to investors from holding such contracts around FOMC announcement days.

3. Monthly continuously compounded returns on the S&P 500 are computed from monthly closing price data in a similar manner to equation (1).

4. The realized variance is computed as the sum of squared high frequency (five minute) returns. Monthly data for the variance risk premium and realized/implied variance is obtained from Hao Zhou’s website. We thank the author for making the data available.

5. We also test for unbiasedness and efficiency of federal funds futures in predicting the federal funds rate. Regression results (available from the authors upon request) indicate that unbiasedness and efficiency cannot be rejected for the one-month-ahead contract used in computing monthly monetary policy shocks.

6. A lag order of two for $Y_t$ is selected by AIC. Using a VARX(1,0) yields similar results.
7. As argued in Bessembinder and Seguin (1993) and given that extracting the unexpected component of the futures-trading volume is the primary goal, using an AR model with arbitrarily long lags would be sufficient. We note that our results are unchanged when we use a well specified ARMA model. Our impulse responses are also not affected when we detrend S&P 500 futures volume by subtracting from it its one or two-year moving averages instead of log differencing.

8. Bernanke and Kuttner (2005) argue that the $MP$ shocks, computed in equation (4), respond significantly to employment news prior to 1994. We therefore follow Bernanke and Kuttner (2005) and consider the component of the $MP$ series that is orthogonal to employment news to be the monetary policy shocks series. Specifically, we regress the $MP$ shocks series in equation (4) on the standardized difference between the median survey forecast and the (as) reported nonfarm employment numbers obtained from the Money Market Services (MMS) survey. The resulting serially uncorrelated residuals series is orthogonal to all the variables in the information set at time $t-1$. As a result, the first equation in the near-VAR model imposes that the monetary policy shocks ($MP$) are uncorrelated and contains only a constant. The rest of the near-VAR model regresses $Y_t$ on three of its lags. Seemingly unrelated regression (SUR) is used to estimate the resulting model. For more details, see Basu, Fernald and Kimball (2006).

9. Bollerslev, Gibson and Zhou (2011) provide empirical evidence that macroeconomic factors and yield spreads affect the variance risk premium. The significance of the yield spreads in affecting the variance risk premium implies that monetary policy changes can also significantly affect market-wide risk aversion.
10. We abstract from denoting the variables with the subscript $n$ (to refer to daily data) and use the subscript $t$ instead for notational simplicity.
BIBLIOGRAPHY


Goto, S., & Valkanov, R. (2002). The Fed’s effect on excess returns and inflation is bigger than you think, Discussion paper, Anderson School of Management, University of California Los Angeles.


Responses to MP

FIGURE 1. Response of excess returns on the S&P 500 (ER), stock market volatility (VOL), variance risk premium (VRP), the real interest rate (RINT), the dividend yield (DY), the change in the T-bill rate (DTB), financial leverage (LEVERAGE) and unexpected futures-trading volume (VOLUME) to a one standard deviation monetary policy shock (MP) as computed from the VAR model in equation (7). Dashed lines are 95% confidence bands constructed using the Monte Carlo simulation method of Sims and Zha (1999).
### Table I

Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>First-Order Autocorrelation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Returns on S&amp;P 500 (ER)</td>
<td>0.31</td>
<td>3.96</td>
<td>-0.03</td>
</tr>
<tr>
<td>Volatility of S&amp;P 500 (VOL)</td>
<td>14.35</td>
<td>6.66</td>
<td>0.68</td>
</tr>
<tr>
<td>VIX Implied Volatility (IVOL)</td>
<td>18.94</td>
<td>6.32</td>
<td>0.84</td>
</tr>
<tr>
<td>Variance Risk Premium (VRP)</td>
<td>16.77</td>
<td>16.10</td>
<td>0.34</td>
</tr>
<tr>
<td>Monetary Policy Shocks (MP)</td>
<td>-0.03</td>
<td>0.09</td>
<td>0.16</td>
</tr>
<tr>
<td>Real Interest Rate (RINT)</td>
<td>0.10</td>
<td>0.24</td>
<td>0.38</td>
</tr>
<tr>
<td>Change in 3-month T-bill Rate (DTB)</td>
<td>-0.02</td>
<td>0.19</td>
<td>0.44</td>
</tr>
<tr>
<td>Dividend Yield on S&amp;P 500 (DY)</td>
<td>2.09</td>
<td>0.71</td>
<td>0.99</td>
</tr>
<tr>
<td>Change in S&amp;P 500 futures trading volume (VOLUME)</td>
<td>0.00</td>
<td>0.15</td>
<td>-0.04</td>
</tr>
<tr>
<td>Commercial and Industrial Loan Growth (LEVERAGE)</td>
<td>0.37</td>
<td>0.79</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Notes: The table provides the descriptive statistics used in the VAR estimation. The sample period extends from January 1990 to December 2007. All variables are in percent.
Table II
Forecast Error Variance Decomposition

<table>
<thead>
<tr>
<th>By Innovation In</th>
<th>ER</th>
<th>VOL</th>
<th>VRP</th>
<th>RINT</th>
<th>DY</th>
<th>DTB</th>
<th>LEVERAGE</th>
<th>VOLUME</th>
</tr>
</thead>
<tbody>
<tr>
<td>ER</td>
<td>87.18</td>
<td>28.33</td>
<td>38.12</td>
<td>0.81</td>
<td>44.50</td>
<td>10.45</td>
<td>0.98</td>
<td>13.48</td>
</tr>
<tr>
<td>VOL</td>
<td>0.26</td>
<td>62.18</td>
<td>22.71</td>
<td>2.00</td>
<td>4.95</td>
<td>0.98</td>
<td>12.55</td>
<td></td>
</tr>
<tr>
<td>VRP</td>
<td>3.47</td>
<td>2.06</td>
<td>34.10</td>
<td>3.86</td>
<td>3.79</td>
<td>3.08</td>
<td>3.92</td>
<td>1.20</td>
</tr>
<tr>
<td>RINT</td>
<td>0.34</td>
<td>0.26</td>
<td>0.86</td>
<td>83.53</td>
<td>4.72</td>
<td>2.53</td>
<td>2.01</td>
<td>0.89</td>
</tr>
<tr>
<td>DY</td>
<td>0.02</td>
<td>0.08</td>
<td>0.28</td>
<td>0.41</td>
<td>22.02</td>
<td>0.20</td>
<td>0.19</td>
<td>0.41</td>
</tr>
<tr>
<td>DTB</td>
<td>0.25</td>
<td>2.55</td>
<td>0.75</td>
<td>0.59</td>
<td>0.10</td>
<td>64.24</td>
<td>12.86</td>
<td>0.44</td>
</tr>
<tr>
<td>LEVERAGE</td>
<td>2.56</td>
<td>0.48</td>
<td>0.62</td>
<td>4.16</td>
<td>5.48</td>
<td>0.06</td>
<td>72.64</td>
<td>1.05</td>
</tr>
<tr>
<td>VOLUME</td>
<td>0.08</td>
<td>0.64</td>
<td>1.27</td>
<td>1.00</td>
<td>0.22</td>
<td>2.11</td>
<td>1.73</td>
<td>68.29</td>
</tr>
<tr>
<td>MP</td>
<td>5.79</td>
<td>3.37</td>
<td>1.25</td>
<td>3.59</td>
<td>18.66</td>
<td>12.33</td>
<td>4.62</td>
<td>1.65</td>
</tr>
</tbody>
</table>

Notes: The forecast error variance decomposition gives the percentage of the variance of the independent variables explained by a shock to one the VARX(p,q)’s variables in equation (7) over a twelve month horizon. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.
Table III

Bivariate GARCH of stock market and Federal funds futures volatility

<table>
<thead>
<tr>
<th>Bivariate GARCH: Dependent Variables</th>
<th>$R_t \Delta FFF_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Equation</td>
<td></td>
</tr>
<tr>
<td>$\mu_R$</td>
<td>0.0510***</td>
</tr>
<tr>
<td></td>
<td>(0.0114)</td>
</tr>
<tr>
<td>$\mu_F$</td>
<td>-0.0390</td>
</tr>
<tr>
<td></td>
<td>(0.0383)</td>
</tr>
<tr>
<td>Variance Equation</td>
<td></td>
</tr>
<tr>
<td>$\omega_R$</td>
<td>0.0061***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
</tr>
<tr>
<td>$\omega_F$</td>
<td>0.0850***</td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
</tr>
<tr>
<td>ARCH Coefficients</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{RR}$</td>
<td>0.0458***</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
</tr>
<tr>
<td>$\alpha_{RF}$</td>
<td>0.0027**</td>
</tr>
<tr>
<td></td>
<td>(0.0012)</td>
</tr>
<tr>
<td>$\alpha_{FR}$</td>
<td>-0.0127**</td>
</tr>
<tr>
<td></td>
<td>(0.0053)</td>
</tr>
<tr>
<td>$\alpha_{FF}$</td>
<td>0.0488***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
</tr>
<tr>
<td>GARCH coefficients</td>
<td></td>
</tr>
<tr>
<td>$\beta_{RR}$</td>
<td>0.9517***</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
</tr>
<tr>
<td>$\beta_{RF}$</td>
<td>-0.0765***</td>
</tr>
<tr>
<td></td>
<td>(0.0097)</td>
</tr>
<tr>
<td>$\beta_{FR}$</td>
<td>-3.5098***</td>
</tr>
<tr>
<td></td>
<td>(0.0543)</td>
</tr>
<tr>
<td>$\beta_{FF}$</td>
<td>0.9655***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-16608.44</td>
</tr>
<tr>
<td>Tse Test for Constant Correlation ($p$-value)</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Notes: The table provides the results from estimating the bivariate GARCH model in equations (8), (9) and (10). Standard errors are in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. The last column is the $p$-value from Tse (2000)’s test for the null of constant correlation.