The Response of Stock Market Volatility to Monetary Policy Shocks

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SUMMARY

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 volatility risk premium to monetary policy. The increase in futures-trading volume appears to be the most important factor for the short-term increase in volatility. 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, monetary policy, 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; D'Amico and Farka, 2011; 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-

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[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).

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 would, 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 Heteroskdasticity (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 (volatility 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 monetary policy shocks on stock market volatility and the volatility risk premium. We employ a recursively identified vector autoregressive (VAR) model which incorporates a monthly measure of aggregate stock market volatility.[2] We additionally examine the channels through which monetary policy shocks affect stock market volatility by studying the joint response of several financial variables to market-based measures of monetary policy shocks. Specifically, we compute monetary policy shocks from federal funds futures data, thus avoiding the need to resort to identifying assumptions, and assess their dynamic impact on trading volume, returns, interest rates and a measure of leverage.

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 0.75%. The results illustrate the asymmetric return-volatility relationship and demonstrate that monetary policy exerts an effect on the volatility 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 (volatility 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

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[2] Previous efforts in the literature (D’Amico and Farka, 2011; Goto and Valkanov, 2002; Thorbecke, 1997) concentrate on augmenting such VARs with monthly stock returns.

increasing popularity with investors[3] shows that volatility, in its own right, is being treated as an underlying asset. 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.

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 Macroeconomic and interest rate data

As widely used in the monetary VAR literature, a measure of aggregate economic activity, inflation and a monetary policy instrument are included as a minimum set of variables for properly identifying monetary policy shocks in VARs. The variables used in the VAR estimation are: the change in the index of leading indicators (DLCOM), industrial production growth (*IPG)*, inflation (*INF*), excess returns on the S&P 500 (*ER*), the volatility of S&P 500 returns (*VOL*), the implied volatility of S&P 500 prices as measured via the VIX index (*IVOL*), the one-month-ahead federal funds futures rate (*FFF*) and the federal funds rate (*FFR*) for the period extending from January 1989 to December 2007.[4] Figure 1 displays the time series dynamics of our macroeconomic and financial variables.

[Insert Figure 1 here]

The sample period considered corresponds to a federal funds rate targeting procedure (Bernanke and Mihov, 1998; Thornton, 2006) and excludes the October 1987 stock market crash.[5]

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[3] Such as the Chicago Board of Options Exchange (CBOE)'s derivatives on the popular VIX (market "fear gauge") index.

[4] Monthly data is obtained the Federal Reserve of St. Louis Economic Database (FRED). Commodity price and futures data are obtained from the Commodity Research Bureau (CRB). Data on the index of leading indicators and the dividend yield on the S&P 500 are downloaded from Datastream.

[5] The January 1989 starting period of the sample also ensures that the Fed's operating procedure, under the chairmanships of Greenspan and Bernanke, was unchanged across the period considered. Thus, the estimated VAR

2.2 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:[6]

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

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:

$$ER_t = R_t - TB_t\,. \tag{2}$$

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

$$VOL_t = 252 \times \sqrt{\frac{1}{N}\sum_{n=1}^{N} R_{n,t}^2}\,, \tag{3}$$

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

Following Bollerslev, Tauchen and Zhou (2009), we define the volatility risk premium as the difference between implied volatility (*IVOL*), measured via the VIX index,[7] and realized stock market volatility computed in equation (3):

$$VRP_t = IVOL_t - VOL_t\,. \tag{4}$$

Other financial variables are used in the second part of the paper. In addition to excess returns and volatility, we employ the following variables in a VAR model that contains only financial variables: the real interest rate (*RINT*) defined as the difference between the three month T-bill rate and the consumer

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model does not exhibit parameter instability. Our choice of sample period also avoids the instability associated with the recent subprime mortgage crisis.

[6] Monthly continuously compounded returns on the S&P 500 are computed from monthly closing price data in a similar manner.

[7] Following Bandi and Perron (2006), the VIX index is multiplied by $\sqrt{252/365}$ to make the conversion from calendar days to trading days.

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 and Augmented Dickey-Fuller (ADF) unit root tests for the macroeconomic and financial series of interest. The last five rows of Table 1 present the summary statistics of the additional financial variables used in the VAR estimation.

[Insert Table 1 here]

The results in Table 1 indicate that, for most of the variables, the null of a unit root can be rejected at the conventional levels although the Federal funds futures rates, Federal funds rate and the dividend yield exhibit very high persistence that is well documented in the literature. Despite their near unit root behavior, we follow the common practice to model these variables in levels. Table 1 also shows that the volatility risk premium is positive on average and despite the strong persistence in realized and implied volatilities, it exhibits only weak serial correlation.

2.3 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. Gurkaynak, Sack and Swanson (2007) and Hamilton (2009) provide empirical evidence supporting the efficiency of the federal funds futures market.[8] 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.

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[8] 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.

Following Bernanke and Kuttner (2005), a monthly monetary policy shocks series is computed from futures prices. Let $FFF_{n,t}^{1}$ denote the one-month-ahead implied rate for day *n* of month *t*, and $FFR_{n,t}$ denote the Federal funds *target* rate for day *n* in month *t*, the monthly monetary policy shock is given by

$$MP_t = \frac{1}{N}\sum_{n=1}^{N} FFR_{n,t} - FFF_{N,t-1}^{1}, \tag{5}$$

where $FFF_{N,t-1}^{1}$ 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 about 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. Let $FFF_{n,t}^{1}$, $FFF_{n,t}^{2}$ and $FFF_{n,t}^{3}$ denote, respectively, the implied interest rates on day *n* of month *t* from the current (spot), one-month-ahead, two-month-ahead and three-month-ahead federal funds futures contracts. Following Hamilton (2009), we use daily changes in the implied rates, denoted as $\Delta FFF_{n,t}^{i} = FFF_{n,t}^{i} - FFF_{n-1,t}^{i}$ for $i = 1,2,3$ 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 [SVARX(*p*,*q*)] is given by

$$B(L)Y_t = \Gamma(L)X_t + \varepsilon_t, \tag{6}$$

where $B(L) = B_0 - B_1 L - B_2 L^2 - \cdots - B_p L^p$ is a matrix lag polynomial of order p whose roots lie strictly outside the unit circle, $\Gamma(L) = \Gamma_0 + \Gamma_1 L + \Gamma_2 L^2 + \cdots + \Gamma_q L^q$ is a matrix lag polynomial of order q and the $(K \times 1)$ vector ε_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 (6). Imposing a recursive ordering assumption would imply that the contemporaneous impact matrix B_0 is lower triangular and provides enough restrictions to recover the structural shocks from the reduced form disturbances.[9] Several studies have used such an identification scheme to recover monetary policy shocks (Boivin and Giannoni, 2002; Christiano, Eichenbaum and Evans, 1999; Goto and Valkanov, 2002; Thorbecke, 1997).

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 (6). The 95% confidence bands are computed using the Monte Carlo method of Sims and Zha (1999).

Following Brissimis and Magginas (2006), we use the following ordering for the endogenous variables in the VAR:

$$Y_t = \left[DLCOM \quad IPG \quad INF \quad FFR \quad ER \quad VOL \right].$$

In addition, a constant and the first lag of the one-month-ahead federal funds futures rate (*FFF*) are included in the vector X_t as exogenous variables in the VAR. As argued in Brissimis and Magginas

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[9] Here, we do not pursue identification through long-run restrictions given some statistical problems that accompany this identification scheme (see Faust and Leeper, 1997; Gospodinov, 2010; among others).

(2006), the inclusion of the index of leading indicators and the one-month-ahead federal funds futures rate allows the VAR to be forward-looking and to span a larger information set. Given the forward-looking nature of financial markets, using a forward-looking VAR model is essential to gauging the stock market's response to a monetary policy shock. Our ordering scheme implies the following assumptions: the monetary policy instrument (*FFR*) responds contemporaneously to all the macroeconomic variables while macroeconomic variables respond to a shock in the monetary policy instrument only with a time lag. Our identification strategy allows stock market variables to respond contemporaneously to all the variables in the system, while the monetary authorities do not respond contemporaneously to stock market volatility.[10] We note that the ordering of the variables we use is in line with the previous studies investigating the relationship between monetary policy and the stock market (Patelis, 1997; Thorbecke, 1997; Goto and Valkanov, 2002; among others) that place financial variables last in the ordering. The orthogonalized shocks from the *FFR* equation, ε_t^{FFR}, are identified as the monetary policy shocks.

Figure 2 displays, for a horizon of twelve months, the response of volatility, excess returns, inflation and industrial production growth to a one standard deviation (10 basis points increase) contractionary monetary policy (*FFR*) shock obtained from the VARX(*p*,*q*) model in equation (6). The VARX(*p*,*q*) model is estimated with three lags as chosen by the Akaike information criterion (AIC).

[Insert Figure 2 here]

The responses in Figure 2 reveal that following the contractionary monetary policy shock, both industrial production growth and inflation increase.[11] The initial increase in industrial production growth and inflation persists for around two months following which both variables start decreasing. Our results

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[10] In order to assess the plausibility of our identifying assumption, we follow Kilian and Vega's (2011) approach to test for any feedback from the stock market to monetary policy. The difference between the federal funds rate and the lag of the one-month-ahead futures rates is regressed onto the Money Market Services (MMS) survey macroeconomic surprises as well as volatility and returns. The results we obtain (available from the author) lend support to the hypothesis that monetary policy does not respond to returns or volatility as the two variables enter the regression insignificantly with *p*-values of 0.31 and 0.11.

[11] While the initial short-lived increase in industrial production growth following a monetary policy contraction is counterintuitive, prior studies (Brissimis and Magginas, 2006; Goto and Valkanov, 2002; among others) have obtained similar results over comparable sample periods.

confirm the findings of previous studies (Ludvigson, Steindel and Lettau, 2002; Goto and Valkanov, 2002) related to the presence of a small price puzzle in the estimated VARs and to an initial increase in economic activity following a contractionary monetary policy shock. However, we note that similarly to the findings of Brissimis and Magginas (2006), the forward-looking nature of the VAR largely mitigates the severity of the price puzzle.

Figure 2 shows a contemporaneous decrease in excess returns due to the monetary policy shock. In fact, a one standard deviation contractionary shock leads to a contemporaneous decrease of one percentage point in excess returns. The well established (Thorbecke, 1997; D'Amico and Farka, 2011) initial decrease in excess returns is short-lived and lasts for around one month. Several interesting features emerge from the response of stock market volatility to a monetary policy shock. First, an *FFR* shock leads to an increase in volatility peaking at around 0.75% one month after the shock. The response of volatility reverts back to its original level in approximately three months following 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 to an *FFR* shock, while volatility's response is most pronounced one month after the shock. The 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 2 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, 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.

We employ Granger causality tests in an effort to study whether the response of volatility is due to the leverage or volatility feedback effects. Table 2 reports the results from Granger causality tests and forecast error variance decompositions resulting from the estimated VARX(p,q) model in equation (6).

[Insert Table 2 here]

Interestingly, the results in Panel A of Table 2 indicate unidirectional causality running from excess returns to volatility. This, in turn, suggests that excess returns contain predictive power for future volatility and that monetary policy's effect on stock market volatility possibly transmits through the returns channel. The unidirectional causality running from stock returns to volatility is more consistent with the leverage effect than with the volatility feedback effect. The forecast error variance decompositions in Panel B of Table 2 shed additional light on the response of stock market volatility to monetary policy shocks. The results from the variance decomposition indicate that monetary policy shocks account for 5.12% of the variance of returns while only 1.93% of the variance of volatility can be traced to innovations in *FFR*. Innovations in volatility (returns) account for 2.78% (6.22%) of the variance of economic activity while their effect on inflation is more modest. When considered jointly, macroeconomic variables account for around 21% of the variance of returns while only 10% of the variance of volatility can be traced to macroeconomic innovations. The bulk of the response of volatility

(27.44%) is due to innovations in excess returns. The empirical evidence in Table 2 suggests that the response of volatility to monetary policy shocks is driven, at least in part, by the latter's effect on returns and seems to be consistent with the leverage effect hypothesis. However, it is possible for the volatility feedback and leverage effect to operate simultaneously as argued in Wu (2001).

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 volatility risk premium, in particular, because it is viewed by market participants as a market-wide measure of risk aversion (Rosenberg and Engle, 2002; Bollerslev, Tauchen and Zhou, 2009; Bollerslev, Gibson and Zhou, 2011). Bollerslev, Gibson and Zhou (2011) provide empirical evidence that macroeconomic factors and yield spreads affect the volatility risk premium. The significance of the yield spreads in affecting the volatility risk premium implies that monetary policy changes can also significantly affect market-wide risk aversion.

In order to investigate the response of the volatility risk premium to monetary policy shocks, we re-estimate the forward-looking VAR by replacing stock market volatility by the volatility risk premium (*VRP*) computed as in equation (4). The response of the volatility risk premium to a monetary policy shock is depicted in Figure 3.

[Insert Figure 3 here]

Figure 3 shows an initial increase in the volatility risk premium following the monetary policy shock. After the initial increase, the volatility risk premium becomes negative one month following the monetary policy shock. It is interesting to note the converse effect that a monetary policy shock exerts on the volatility risk premium and volatility itself. The spike in volatility corresponds very closely with the decrease in the volatility risk premium with both occurring one month after the shock. The impulse responses suggest the following dynamics: a monetary policy shock, which constitutes a negative surprise to stocks, increases risk aversion at first. Nonetheless, the monetary policy shock also serves as a signal to investors that the Fed expects a growing economy. This, in turn, leads to a decrease in the volatility risk premium one month after the shock as the positive outlook for the economy leads to a decrease in the uncertainty and calms down the markets. Our results are indicative that monetary policy changes also significantly affect risk premiums. The evidence presented thus far suggests that leverage and volatility feedback effects contribute to changes in volatility.

It is also plausible the responses of volatility and returns are due to the indirect influence monetary policy changes exert on trading volume, dividends, or the discount rate. We turn next to a more complete investigation of the different transmission channels of monetary policy shocks to volatility.

3.2 VAR model with financial variables: the transmission of monetary policy to volatility

In view of the effect of monetary policy on volatility, the volatility risk premium and excess stock returns established in Section 3.1, we aim to disentangle the channels of transmission of monetary policy 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 ER_t denote excess returns at time *t*. Then, following Bernanke and Kuttner (2005) excess returns can be written as:

$$ER_t - E_t(ER_{t+1}) = \left(E_{t+1} - E_t\right)\left\{\sum_{j=0}^{\infty} \rho^j \Delta D_{t+1+j} - \sum_{j=1}^{\infty} \rho^j RINT_{t+1+j} - \sum_{j=1}^{\infty} \rho^j ER_{t+1+j}\right\}, \qquad (7)$$

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 ρ 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 (7) 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 before, 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 examine the transmission of monetary policy to volatility, we use the variables included in equation (7) as a starting point and employ a VAR consisting solely of financial variables. Following Bernanke and Kuttner (2005), we employ the following VAR model to assess monetary policy shocks' effect (MP_t),[12] computed from equation (5), on financial variables:

$$Y_t = A_1 Y_{t-1} + \Phi_0 MP_t + \omega_t \,, \tag{8}$$

where $Y_t = \left[ER \quad RINT \quad DTB \quad VOLUME \quad LEVERAGE \; VOL \quad DY\right]$. In addition to excess returns, volatility, 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 S&P 500 futures-trading volume. Bessembinder and Seguin (1993) provide empirical evidence for 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.[13] In equation (8), Φ_0 summarizes the contemporaneous response of Y_t to an exogenous monetary policy shock.

The use of the VAR model in equation (8) in place of the forward-looking VAR is motivated by several reasons. First, the financial variables of interest cannot be included in the forward-looking VAR as this would entail estimating a large number of parameters and leads to degrees of freedom problems.

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[12] A lag order of three for Y_t is selected by AIC. Using a VARX*(1,0)* yields similar results.

[13] As argued in Bessembinder and Seguin (1993), 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.

Embedding the monetary policy shocks as an exogenous variable in the VAR circumvents the need to estimate a large VAR model in order to properly identify the monetary policy shocks. Second, the VAR model in equation (8) allows for analyzing the joint dynamics of several financial variables to a monetary policy shock. This desirable feature of the model permits a closer inspection of the channels through monetary policy shocks affect the stock market. Third, as argued in Bernanke and Kuttner (2005), using the VAR model in equation (8) is equivalent to placing the monetary policy instrument (*FFR*) first in a VAR model such as equation (6). By including monetary policy shocks computed from futures data, we simultaneously avoid the need to resort to identifying assumptions and test the robustness of our results with respect to a change in the monetary policy instrument's ordering in the VAR.

The effect of the monetary policy shock at time *t* on Y_{t+j} is measured by $A_1^j \Phi_0$. 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[14] 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 is displayed in Figure 4.

[Insert Figure 4 here]

The responses of excess returns and volatility to a monetary policy shock computed from federal funds futures bear similarity to those of the forward-looking VAR. Namely, we find that excess returns decrease contemporaneously by around 1.0% due to a monetary policy shock whereas volatility's response peaks

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[14] 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 (5) 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).

one month following the shock at 0.75%. Once more, the results demonstrate the asymmetric return-volatility relationship.[15]

Similarly to excess returns, 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 four months following the shock. The dynamics of the real interest rate show an initial contemporaneous increase followed by a brief decrease two months after the shock. The real interest rate then turns and remains positive for twelve months. 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.

We argue in Section 3.1 that the causality tests reported in Table 2 are consistent with monetary policy shocks transmitting through the leverage channel. Figure 4 lends additional 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.

Figure 4 also shows that the unexpected S&P 500 futures-trading volume 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 negative. A closer inspection of the joint dynamics of volatility and volume reveals that the increase in the trading volume is associated with an increase in volatility (first two months following the shock). Volatility decreases when trading volume becomes negative. The positive relationship between futures-trading activity and volatility is consistent

---

[15] One notable difference is the increased persistence in the response of volatility which does not die out twelve months after the shock. The increased persistence in the response of volatility is suggestive of possible profit opportunities for investors seeking to treat volatility as an asset.

with Bessembinder and Seguin (1993) and with the notion that the monetary policy shock constitutes new information arrival into the market and 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 4 uncover that the discount (interest) rate, leverage and dividend channel all contribute to the increase in volatility. In order to better assess the strength of each of the channels, Table 3 provides the forecast error variance decompositions from the VARX*(p,q)* in equation (8).

[Insert Table 3 here]

The variance decompositions in Table 3 show that monetary policy shocks account for 11.18% and 10.77% of the variance of excess returns and volatility, respectively. Whereas a monetary policy shock accounts for 13.17% of the variance of financial leverage and 11.56% of the variance of the T-bill rate, only a small proportion of the variances of the futures-trading volume or the real interest rate are explained by an *MP* shock.

The variance decomposition of stock market volatility shows that, aside from shocks to volatility itself, futures-trading volume accounts for the biggest proportion of the variance of volatility. Innovations to financial leverage amount to explaining only 1.91% of the variance of volatility. While our findings document an important role for monetary policy in affecting returns and volatility, they cast doubt on ascribing the bulk of stock market volatility's response to financial leverage and are suggestive of an important role for trading volume in affecting short-term volatility dynamics.

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 innovations) 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). The persistent increase in the dividend yield drives excess returns and volatility to revert back to their mean.

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 sections, we turn next to investigating the relationship among the stock market and monetary policy expectations 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 1989 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 heteroskdasticity 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 market 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 shock 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):

$$\begin{bmatrix} R_t \\ \Delta FFF_t \end{bmatrix} = \begin{bmatrix} \mu_R \\ \mu_F \end{bmatrix} + \begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{F,t} \end{bmatrix} \tag{9}$$

$$\begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{F,t} \end{bmatrix} = \begin{bmatrix} h_{R,t}^{1/2} & 0 \\ 0 & h_{F,t}^{1/2} \end{bmatrix} \begin{bmatrix} \eta_{R,t} \\ \eta_{F,t} \end{bmatrix} \tag{10}$$

$$\begin{bmatrix} h_{R,t} \\ h_{F,t} \end{bmatrix} = \begin{bmatrix} \omega_R \\ \omega_F \end{bmatrix} + \begin{bmatrix} \alpha_{RR} & \alpha_{RF} \\ \alpha_{FR} & \alpha_{FF} \end{bmatrix} \begin{bmatrix} \varepsilon_{R,t-1}^2 \\ \varepsilon_{F,t-1}^2 \end{bmatrix} + \begin{bmatrix} \beta_{RR} & \beta_{RF} \\ \beta_{FR} & \beta_{FF} \end{bmatrix} \begin{bmatrix} h_{R,t-1} \\ h_{F,t-1} \end{bmatrix}, \tag{11}$$

where $\eta_{R,t}$ and $\eta_{F,t}$ 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, ΔFFF_t denotes the daily changes in the implied interest rates from the one, two or three-month-ahead federal funds futures contracts described in Section 2.3 and $h_{R,t}$ and $h_{F,t}$ denote the conditional volatilities of stock returns and federal funds futures, respectively.[16] 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, α_{RF} and α_{FR} measure the effect of cross squared residuals on volatility whereas β_{RF} and β_{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 α_{RF} and β_{RF}.

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[16] We abstract from denoting the variables with the subscript *n* (to refer to daily data) and use the subscript *t* instead for notational simplicity.

The results from estimating the bivariate GARCH model in equations (9), (10) and (11) are reported in Table 4.

[Insert Table 4 here]

In line with Hamilton (2009), the results indicate strong GARCH effects in the daily changes in federal funds futures as evidenced by the large and significant β_{FF} coefficient on lagged federal funds futures volatility. Both cross volatility coefficients, β_{RF} and β_{FR}, are highly significant and point to a bidirectional relationship between stock market and federal funds futures volatility. The estimate of β_{RF} suggests that, for the spot and one-month-ahead futures contract, 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 β_{FR}, for the one-month-ahead futures contract indicates that higher stock market volatility increases 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. Schwert (1989) analyzes the effect of real macroeconomic volatility on stock return volatility and finds weak evidence, at the monthly level, that macroeconomic volatility predicts stock return volatility. More specifically, Schwert (1989) argues that the short-term interest rate volatility does not possess predictive power for stock market volatility. Our results differ from those of Schwert (1989) along two dimensions. First, our analysis is undertaken at the daily level and uses a different sample. Second, we investigate the effect of volatility of a futures contract written on the monetary policy rate set by the Fed on stock market volatility while Schwert (1989) uses the commercial paper rate to measure short-term interest rate volatility. Due to efficiency of the near-term Federal funds futures (Hamilton, 2009; Gurkaynak, Sack and

Swanson, 2007), they also implicitly summarize markets participants' expectations about future inflation and real output growth, both of which are variables the Fed takes into account when making a monetary policy decision. Federal funds futures rates thus subsume a richer information set than commercial paper rates.

The results in Table 4 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 recursively identified vector autoregression, our findings uncover a significant response of stock market volatility to monetary policy shocks. Our results show an asymmetric response of volatility and returns to a monetary policy shock and reveal an important response of the volatility risk premium, and by extension, of risk aversion, to monetary policy. In addition, we study the channels through which monetary policy affects stock market volatility. Our findings suggest that while monetary policy increases discount rates and leverage it is the increase in trading volume that is the most important factor for the short-term increase in volatility. Following the initial effect of monetary policy on trading volume, the dynamic responses of excess returns and volatility are dominated by the persistent effect of monetary policy on stock market fundamentals (dividends or leverage). In light of the important 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 volatility risk premium. This, in turn, implies that the Fed might be able to reduce stock market volatility and to influence market-wide risk aversion through better communication or increased transparency. From a trading perspective, our results show that investors with a correct anticipation of possible Fed actions might be able to trade profitably, by entering into suitable options positions, due to the 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, by treating volatility itself as an underlying asset.

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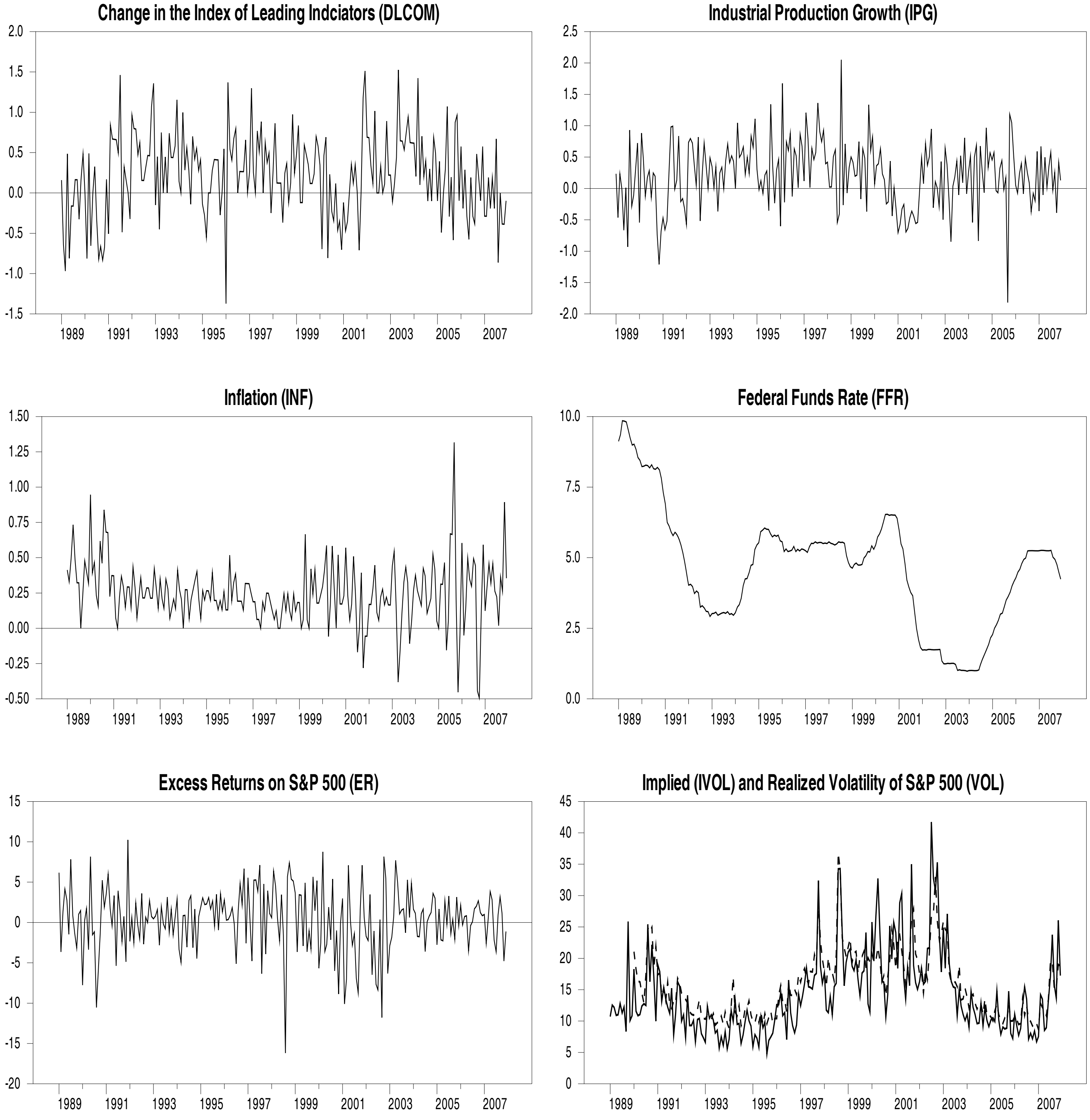


Change in the Index of Leading Indciators (DLCOM)

Industrial Production Growth (IPG)

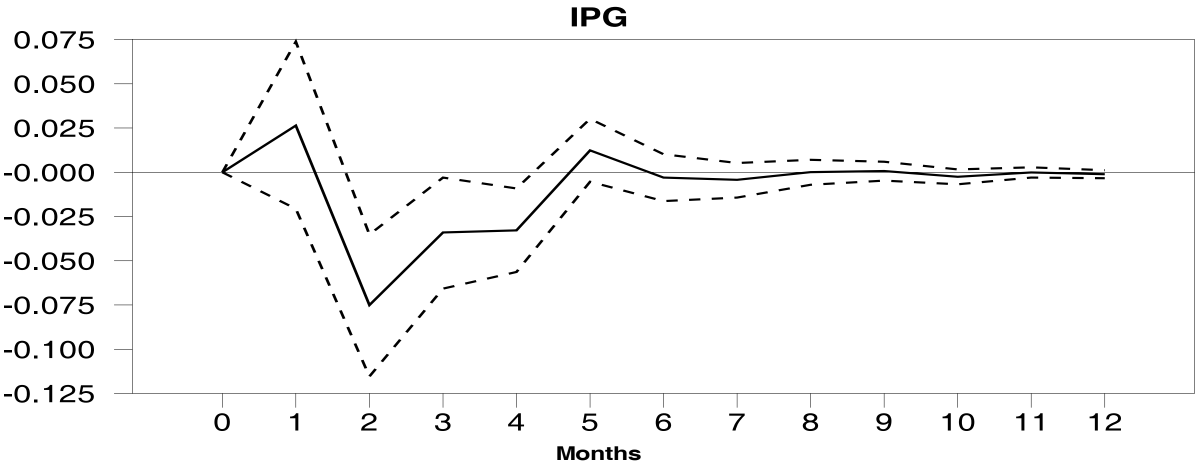
Inflation (INF)

Federal Funds Rate (FFR)

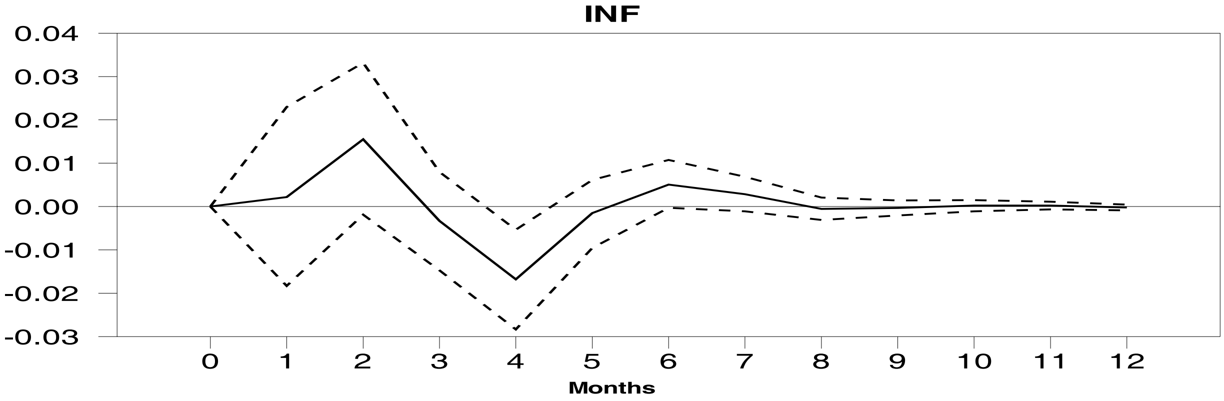
Excess Returns on S&P 500 (ER)

Implied (IVOL) and Realized Volatility of S&P 500 (VOL)

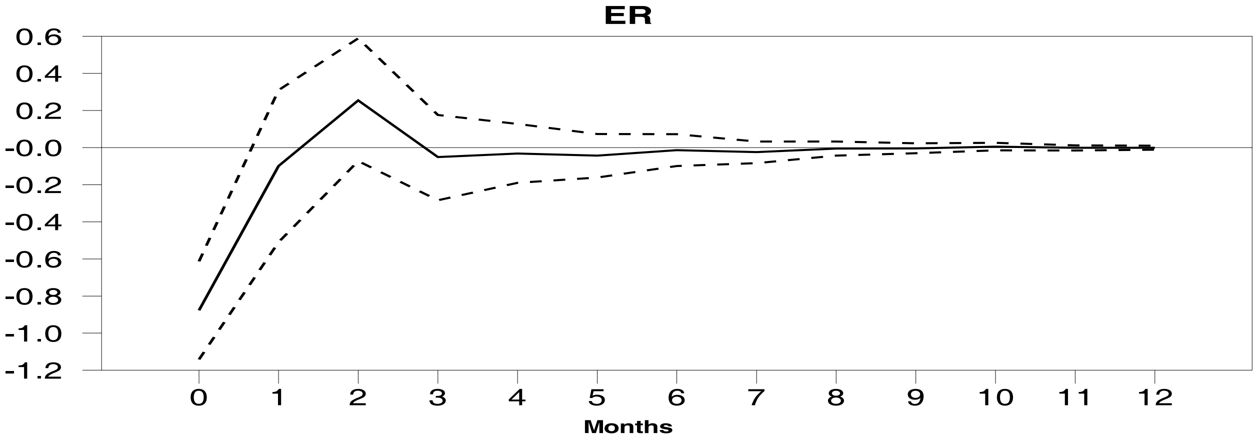
Figure 1. Monthly time series of the macroeconomic and financial variables: January 1989 to December 2007


IPG

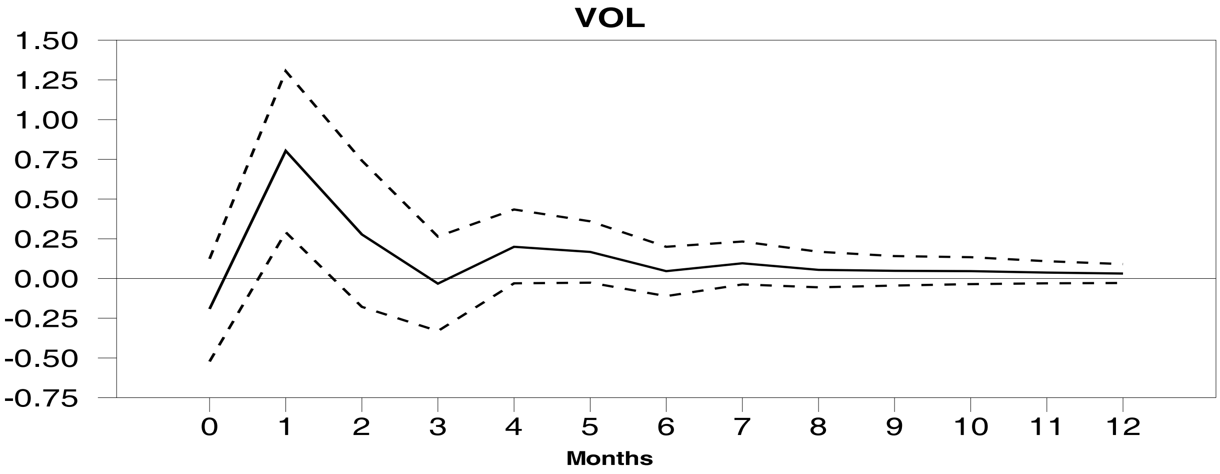
0.075
0.050
0.025
-0.000
-0.025
-0.050
-0.075
-0.100
-0.125
0
1
2
3
4
5
6
7
8
9
10
11
12
Months


INF

0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
0
1
2
3
4
5
6
7
8
9
10
11
12
Months


ER

0.6
0.4
0.2
-0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
0
1
2
3
4
5
6
7
8
9
10
11
12
Months



Responses to FFR

Figure 2. Response of industrial production growth (IPG), inflation (INF), excess returns on the S&P 500 (ER) and volatility of S&P 500 (VOL) to a one standard deviation monetary policy (FFR) shock. Dashed lines are 95% confidence bands constructed using the Monte Carlo simulation method of Sims and Zha (1999).

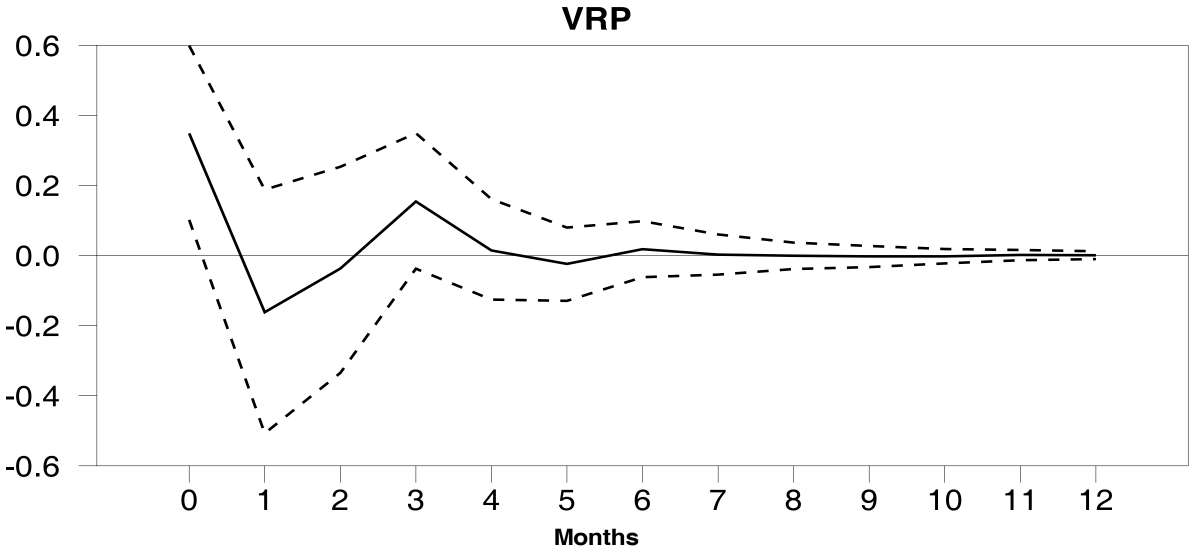
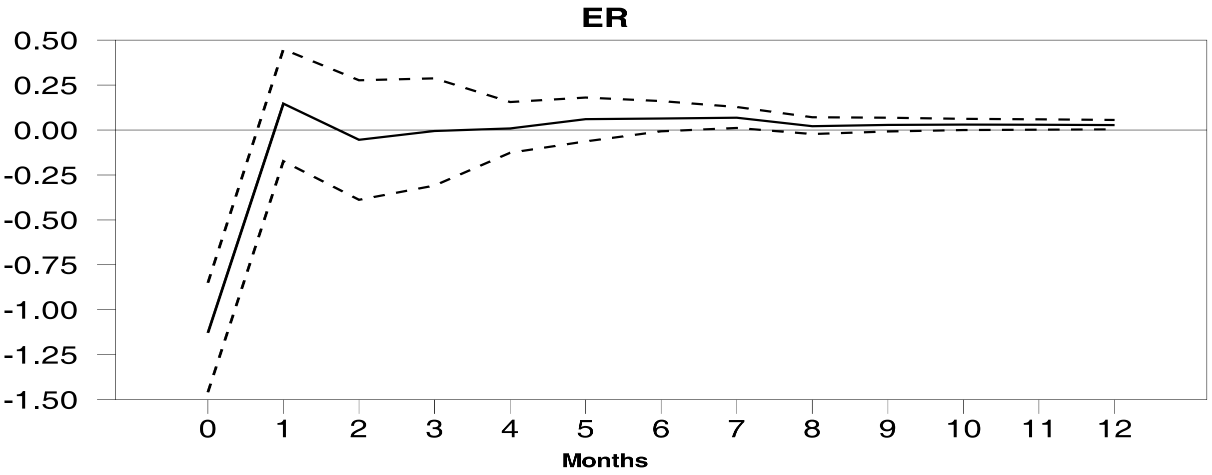


Figure 3. Response of the volatility risk premium (VRP) to a one standard deviation monetary policy (FFR) shock. Dashed lines are 95% confidence bands constructed using the Monte Carlo simulation method of Sims and Zha (1999).


ER
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0.25
0.00
-0.25
-0.50
-0.75
-1.00
-1.25
-1.50
0
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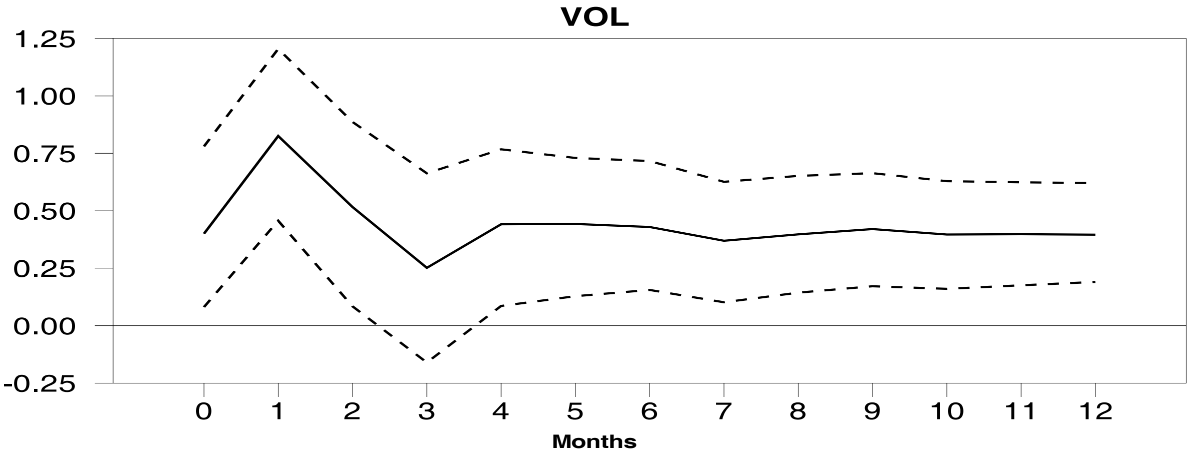
2
3
4
5
6
7
8
9
10
11
12
Months


VOL
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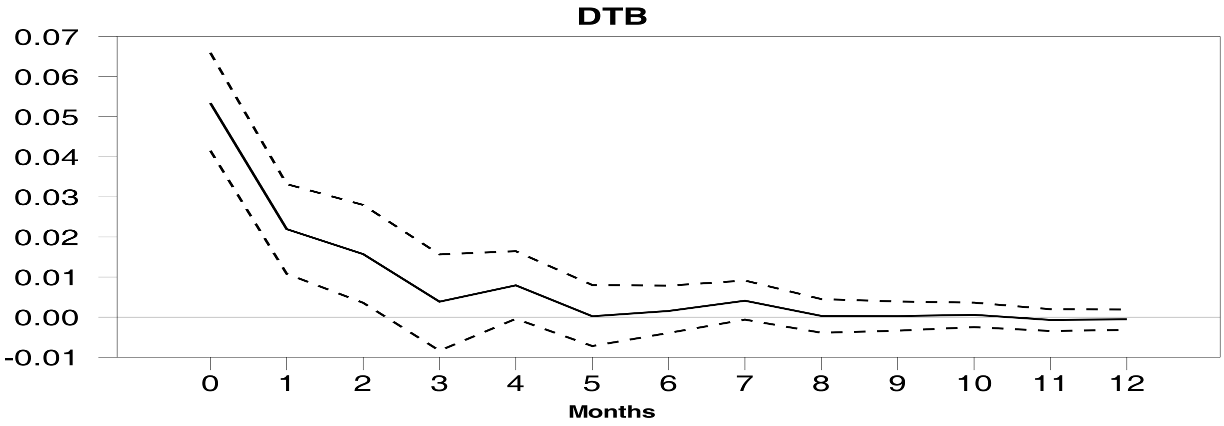
1.00
0.75
0.50
0.25
0.00
-0.25
0
1
2
3
4
5
6
7
8
9
10
11
12
Months


DTB
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0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
0
1
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3
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5
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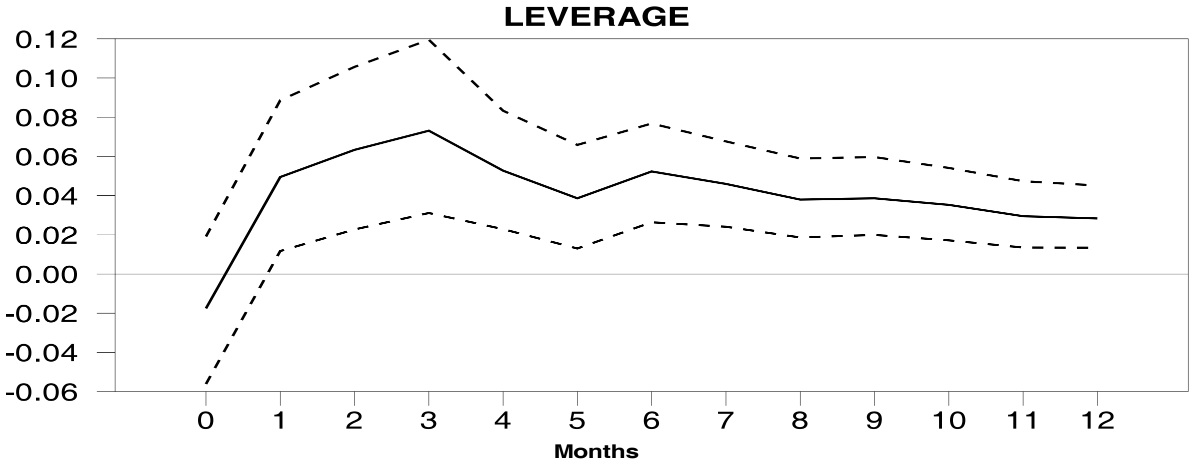
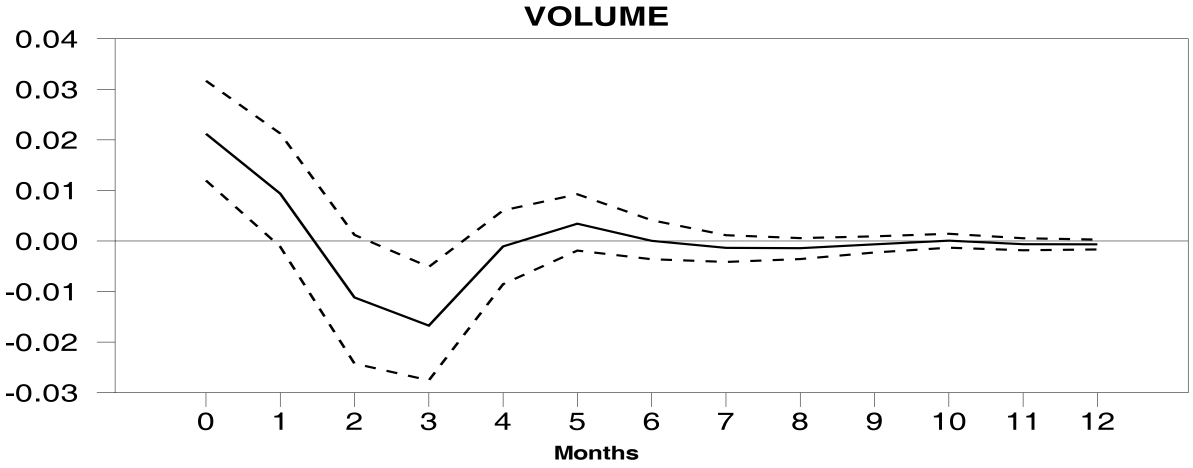
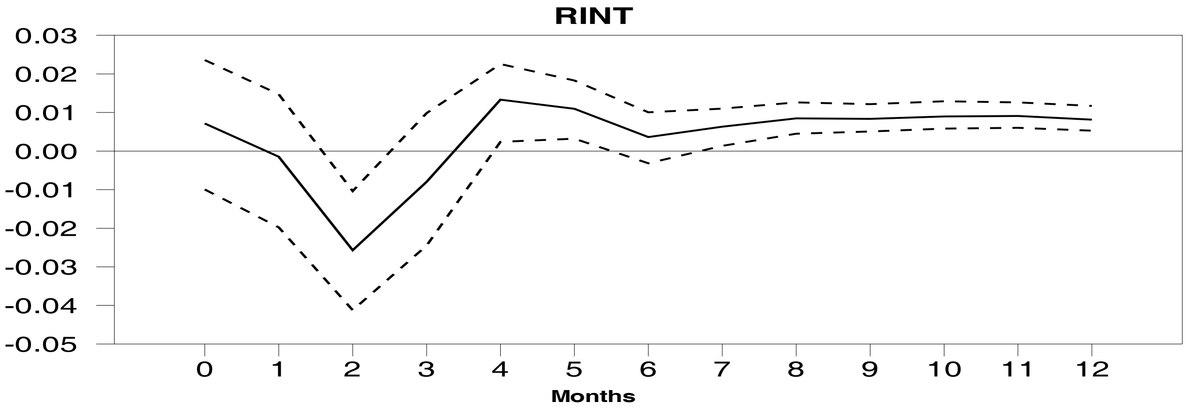
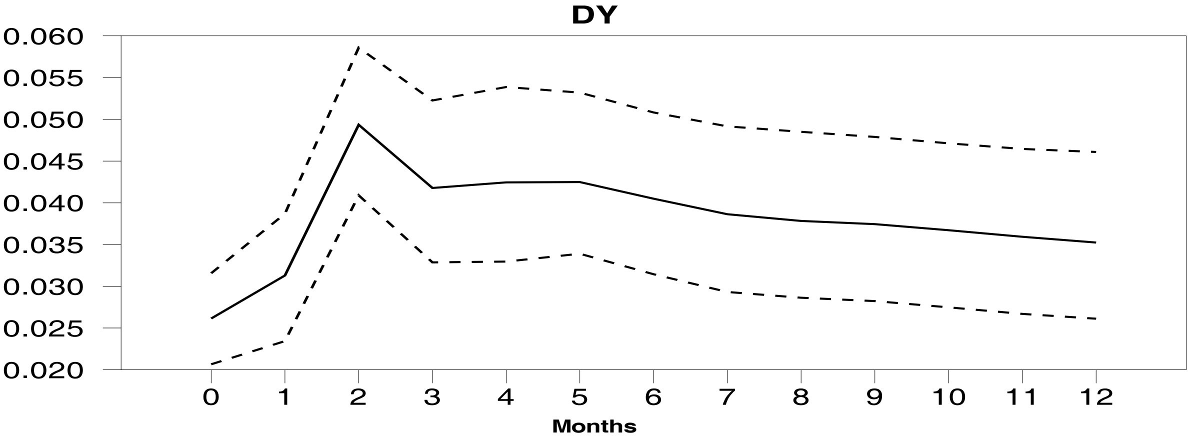
8
9
10
11
12
Months


LEVERAGE


VOLUME


RINT



Responses to MP

Figure 4. Response of excess returns on the S&P 500 (ER), stock market volatility (VOL), the change in the T-bill rate (DTB), financial leverage (LEVERAGE), unexpected futures-trading volume (VOLUME), the real interest rate (RINT) and the dividend yield (DY) to a one standard deviation monetary policy shock (MP) as computed from the model in equation (10). Dashed lines are 95% confidence bands constructed using the Monte Carlo simulation method of Sims and Zha (1999).

Table 1

Summary Statistics and Unit Root Tests

Variable	Mean	Standard Deviation	First-Order Autocorrelation	ADF statistic
Change in Index of Leading Indicators (DLCOM)	0.21	0.50	0.16	-6.09
Industrial Production Growth (IPG)	0.21	0.52	0.08	-6.51
Inflation (INF)	0.24	0.22	0.28	-12.09
Federal Funds Rate (FFR)	4.63	2.09	0.99	-1.62
One-Month Federal Funds Futures Rate (FFF)	4.64	2.07	0.99	-2.87
Excess Returns on S&P 500 (ER)	0.37	3.94	-0.04	-17.25
Volatility of S&P 500 (VOL)	14.25	6.57	0.66	-5.47
VIX Implied Volatility (IVOL)	15.74	5.25	0.84	-4.25
Volatility Risk Premium (VRP)	1.38	3.47	0.13	-5.83
Real Interest Rate (RINT)	0.11	0.24	0.39	-5.30
Change in 3-month T-bill Rate (DTB)	-0.02	0.19	0.44	-4.60
Dividend Yield on S&P 500 (DY)	2.16	0.75	0.99	-2.14
Change in S&P 500 futures trading volume (VOLUME)	0.00	0.46	-0.49	-6.52
Commercial and Industrial Loan Growth (LEVERAGE)	0.37	0.78	0.67	-3.11

Notes: The table provides the summary statistics of the macroeconomic and financial variables used in the VAR estimation. The ADF statistic refers to the Augmented Dickey Fuller test for a unit root with only a constant included in the regression. The optimal lag length for the ADF test is chosen using the Bayesian Information criterion (BIC). The corresponding critical values for the ADF test at the 10%, 5% and 1% significance levels are -2.57, -2.86 and -3.43, respectively. The sample period extends from January 1989 to December 2007. All variables are in percent.

Table 2

Granger Causality Tests and Forecast Error Variance Decompositions for the Forward-Looking VAR

Panel A: Granger Causality F-Tests

	Dependent Variable in the VAR :					
Independent Variables in the VAR:	DLCOM	IPG	INF	FFR	ER	VOL
DLCOM	3.69	6.53***	2.67**	0.13	0.80	0.54
	(0.01)	(0.00)	(0.04)	(0.94)	(0.49)	(0.64)
IPG	1.26	3.51**	0.59	3.02**	0.60	0.42
	(0.28)	(0.01)	(0.61)	(0.03)	(0.61)	(0.73)
INF	1.22	0.74	7.55***	0.77	1.27	0.23
	(0.30)	(0.52)	(0.00)	(0.50)	(0.28)	(0.87)
FFR	4.05***	2.96**	0.40	4.65***	0.17	0.39
	(0.00)	(0.03)	(0.75)	(0.00)	(0.91)	(0.75)
ER	10.77***	2.38*	0.82	1.17	0.26	10.04***
	(0.00)	(0.07)	(0.48)	(0.31)	(0.85)	(0.00)
VOL	0.26	3.20**	2.07	0.08	0.10	50.36***
	(0.84)	(0.02)	(0.10)	(0.96)	(0.95)	(0.00)

Panel B: Forecast Error Variance Decomposition

	Variable Explained:					
By Innovation In:	DLCOM	IPG	INF	FFR	ER	VOL
DLCOM	77.23	18.89	11.75	2.45	7.22	3.32
IPG	1.68	68.19	0.64	5.93	5.75	3.90
INF	1.91	0.68	82.85	1.04	3.14	0.57
FFR	6.80	3.14	1.14	85.58	5.12	1.93
ER	11.93	6.22	1.15	4.85	78.55	27.44
VOL	0.43	2.78	2.46	0.13	0.19	63.01

Notes: The table provides the results of Granger causality tests and forecast error variance decompositions at a twelve month horizon from the VARX(p,q) model in equations (6). The F-test refers to a joint exclusion test for all the lags of one of the independent variables in each equation (independent variable) of the VARX(p,q). Numbers in parentheses are the p-values of the F-test. 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 endogenous variables. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 3

Forecast Error Variance Decomposition for the Financial VAR

Forecast Error Variance Decompositions							
	Variable Explained:						
By Innovation In:	RINT	DY	DTB	VOLUME	LEVERAGE	ER	VOL
RINT	87.96	3.32	3.13	0.93	5.04	3.89	6.21
DY	2.06	31.16	2.44	3.15	0.65	14.42	4.33
DTB	2.83	4.20	71.40	3.41	16.91	0.76	4.65
VOLUME	1.14	2.35	1.84	76.50	8.18	6.57	17.06
LEVERAGE	0.89	9.91	1.18	0.88	54.85	2.57	1.91
ER	1.12	19.79	6.75	5.70	0.52	57.62	10.55
VOL	2.15	0.17	1.66	7.47	0.65	3.32	44.47
MP	1.81	29.07	11.56	1.92	13.17	11.18	10.77

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 (8). * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

Table 4

Bivariate GARCH of stock market and Federal funds futures volatility

Bivariate GARCH: Dependent Variables	R_t,ΔFFF_t^1	R_t,ΔFFF_t^2	R_t,ΔFFF_t^3
Mean Equation			
μ_R	0.0485***	0.0495***	0.0509***
	(0.0105)	(0.0097)	(0.0113)
μ_F	-0.0095	-0.0374	-0.0311
	(0.0078)	(0.0384)	(0.0456)
Variance Equation			
ω_R	0.0090***	0.0062***	0.0089***
	(0.0004)	(0.0015)	(0.0016)
ω_F	0.0001	0.0846***	0.1108***
	(0.0001)	(0.0088)	(0.0170)
ARCH Coefficients			
α_{RR}	0.0622***	0.0455***	0.0535***
	(0.0011)	(0.0043)	(0.0018)
α_{RF}	0.0014	0.0027**	0.0019
	(0.0014)	(0.0012)	(0.0015)
α_{FR}	0.1313***	-0.0115	0.0232
	(0.0042)	(0.0142)	(0.0165)
α_{FF}	0.0871	0.0479***	0.0369***
	(0.0004)	(0.0010)	(0.0027)
GARCH coefficients			
β_{RR}	0.9314***	0.9519***	0.9435***
	(0.0009)	(0.0043)	(0.0016)
β_{RF}	-0.1125***	-0.0650**	-0.1305***
	(0.0279)	(0.0257)	(0.0487)
β_{FR}	1.9528***	-2.8769***	-2.8282***
	(0.0446)	(0.2166)	(0.3923)
β_{FF}	0.9449***	0.9658***	0.9670***
	(0.0001)	(0.0009)	(0.0023)
Log Likelihood	-16263.23	-16687.57	-16982.54
Test for Constant Correlation (*p* -value)	0.19	0.10	0.30

Notes: The table provides the results from estimating the bivariate GARCH model in equations (9), (10) and (11). 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.