"Does Monetary Policy Signal Future Economic Risk? Investigating the Link between Monetary Policy Shocks and Stock Returns"

Tony Caporale & Mark J. Perry

Abstract

We investigate the impact of monetary policy shocks on stock returns using an Arbitrage Pricing Theory framework. After controlling for other risk factors, we find that changes in a monetary policy index measure is a significantly positive risk factor that raises excess returns (risk premiums) on monthly U.S. stocks. We argue that this relationship is due to the signal to financial markets that changes in monetary policy reveal about the Federal Reserve's forecast of future economic activity. Our result lends support to the findings of Romer and Romer (2000), and Peek et al. (2003) that the Fed possesses inside information that is not known to the public.

Introduction

A voluminous literature in monetary economics has emerged which seeks to identify and quantitatively measure the transmission mechanisms of monetary policy (see Mishkin, 1995; Kuttner and Mosser, 2002, for useful surveys). Some of the main channels of monetary policy identified include:

(a) the Interest Rate Channel – which stresses the role of bank lending on investment and aggregate demand,

(b) the Exchange Rate Channel – which argues that policy induced interest rate differentials lead to changes in exchange rates and thus the balance of payments and the overall level of aggregate demand, and

(c) the Wealth Effect Channel – which argues that monetary policy induced changes in asset prices affect aggregate demand through the consumption function. In this essay we provide some new evidence and a different interpretation of the Wealth Effect Channel.

Although the task of documenting and explaining the relationship between monetary policy and asset prices has received considerable attention by financial economists, differences in results, interpretations, and statistical methodologies employed in these studies have prevented the formation of a general consensus on this issue. Rozeff (1974) uses monetary aggregates to measure policy innovations and shows that expansionary policy raises stock returns. In contrast, Black (1993) argues that monetary policy cannot affect equity prices or interest rates. Thorbecke (1997) employs several different measures of monetary policy and various statistical models (ranging from Vector Autoregressions to event studies) to analyze how stock returns respond to monetary shocks. He demonstrates that expansionary policy increases ex-post stock returns and argues that this result can be explained by the positive effect that follows expansionary monetary policy changes. Similar results and conclusions were reached by Patelis (1997) using U.S. data and by Lastrapes (1998) using data for the G-7 countries.

In contrast, Chami *et al*. (1999) recently argued for a negative relationship between monetary policy and stock returns caused by the positive relationship between monetary expansions and inflationary expectations. They explained that higher inflationary expectations reduce the real value of firms' assets by imposing a property tax on stocks in addition to an income tax on dividends, which therefore lowers stock returns.

The analysis presented here relies upon the insights of Romer and Romer (2000), and Peek *et al*. (2003) that the Federal Reserve has a statistically significant and exploitable information advantage over the public about the future state of the economy, and this information is revealed to the financial markets through monetary policy. Although neither Romer and Romer, nor Peek et al., specifically apply their findings to changes in equity prices, their strong evidence of the Fed's significant informational superiority would directly link monetary policy and stock returns through a "central bank information signaling channel."

We investigate the monetary policy-stock return relationship in the U.S. using a quantitative index measure of the stance of U.S. monetary policy recently developed by Bernanke and Mihov (1998). As we explain more fully below, this monetary policy index provides the best opportunity to date for an analysis of this issue that is not tainted by measurement errors with respect to the monetary policy variable. We also, following Elyasiani and Mansur (1998), nest our investigation within the confines of a parsimoniously specified multi-factor Arbitrage Pricing Theory (APT) model. An advantage of the APT model is that it links changes in excess stock returns directly to their sensitivity and exposure to risk factors, and thus serves to help constrain the possible interpretations of the parameter estimates.

Our key empirical result is that changes in monetary policy are priced as a significantly positive risk factor that raises monthly excess returns for U.S. stocks during the 1971-1996 period. Central banks tend to change the stance of monetary policy countercyclically, and our main finding is fully consistent with the view that the wealth effect channel of monetary policy largely reflects the information signal provided by the policy change about future economic activity. If the Fed has a significant information advantage over the public about the current and future state of the economy, a move toward more expansionary (contractionary) monetary policy signals the financial markets of a(n) increase (decrease) in economic risk, which necessitates a rise (fall) in the risk premium (and therefore excess returns). Interestingly, this central bank information signaling explanation would be valid whether or not the policy changes had any real effect on real economic activity. It is also fully consistent with important recent work by Vassalou (2003, forthcoming) who finds that a measure of news about future GDP growth best explains a cross section of equity returns, and dominates other risk factors in an asset pricing model. We argue that "Fed watching" provides a way for economic agents to gather such news.

We proceed as follows: Section II briefly discusses the problems with measuring the stance of monetary policy and presents the Bernanke and Mihov index measure of monetary policy. Section III contains a description of our APT framework, data, statistical methodology and empirical results, and Section IV presents our summary and conclusions.

The Bernanke-Mihov Measure of Monetary Policy

One difficulty with measuring the stance of monetary policy is the potential endogeneity of monetary aggregates. Monetary growth rates reflect endogenous shifts in money demand as well as exogenous policy changes if the Federal Reserve even partially accommodates money demand shocks. One response to the problem of endogeneity has been to abandon monetary aggregates as measures of policy for other more direct measures. For instance, Romer and Romer (1989) use a narrative approach to measure policy contractions. Boschen and Mills (1991) build on this approach to construct a more general variable of monetary policy. An advantage of both Romer and Romer's and Boschen and Mills' indexes is that they are non-parametric: their derivation does not necessitate the modeling of financial institutions or Federal Reserve procedure. Possible disadvantages of these measures of policy include subjectivity and the inability of the indexes to distinguish between endogenous and exogenous policy changes (see Hoover and Perez (1994), for a careful discussion of the problems with these monetary measures).

McCallum (1983), Bernanke and Blinder (1992), Friedman (2000), and Christiano *et al.* (1994), argue that interest rates or interest rate spreads provide better measures of policy innovations than monetary aggregates. A problem with these interest rate measures of policy is that there is little consensus about which interest rate (real or nominal; short or long) best gauges the stance of policy.

In an important study, Bernanke and Mihov (1998) are the first researchers to use a parametric approach to measure the stance of monetary policy that largely avoids many of the problems associated with previous measures discussed above[1]. Bernanke and Mihov's data-based measure of monetary policy utilizes restrictions imposed by central bank operating procedures to identify and estimate a VAR which includes a set of macroeconomic and monetary policy variables. A significant advantage of the Bernanke-Mihov index over alternative policy variables is that it provides a monetary policy measure that adjusts to reflect both the period when the Fed targeted the Federal Funds rate, and the period when non-borrowed reserves were targeted. Their model is used to generate a quantitative monthly index of monetary policy from 1971.01 to 1996.12 (312 observations), which we employ as our measure of monetary policy. Positive index values (170 months) indicate a move toward expansionary policy, and negative index values (142 months) indicate contractionary policy. A graph of the monetary policy index is presented below in Figure 1.

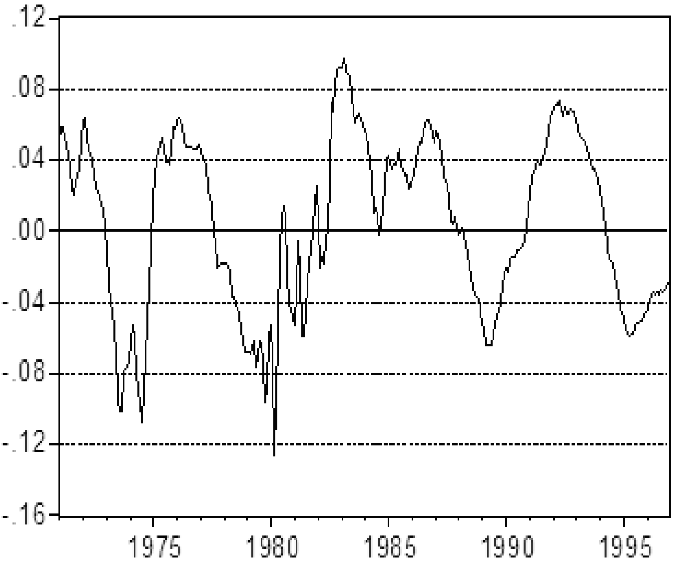
Framework, Data, Model Specification, and Empirical Results

A. *Framework*

A prominent tool used in the finance literature to analyze the variability of asset returns has been the arbitrage pricing theory (APT) proposed by Ross (1976). The APT has proven to be a very flexible framework to analyze asset returns since it allows an asset to be exposed to several risk factors. Each risk factor therefore compensates this asset to the extent of the asset's exposure to this risk factor. Equation (1) below presents the basic APT model:

$$\mathrm{ER}_i = b_{1i}\delta_1 + \ldots + b_{ki}\delta_k + \epsilon_i \tag{1}$$

Figure 1
Monetary Policy Index, 1971.01 to 1996.12



[1] See Bernanke and Mihov (1998) for the details concerning the assumptions behind the construction of the policy index as well as the empirical estimation procedure.

where ER_i is the excess return on Asset i: the total return minus the risk free interest rate, $b_{1i} \ldots b_{ki}$ are the reactions in Asset i's excess return to movements in common risk factors $\delta_1 \ldots \delta_k$, and ϵ_i is a stochastic error term or an idiosyncratic effect on Asset i's return which by assumption is completely diversifiable in large portfolios.

Risks (or common risk factors, using APT terminology) come from various sources. Although Ross (1976) and his followers propose a statistical procedure to model common risk factors by analyzing a variance-covariance matrix of an N-asset portfolio, others have investigated these risk factors by using economic theory (Thorbecke, 1997). We next construct a specific APT model to investigate the potential effects of monetary policy, interest rates, and various measures of uncertainty on excess stock returns.

B. *Data*

The sample period that we consider consists of 312 monthly observations from January 1971 to December 1996 for the following variables: Excess Returns (ER) is the difference between the total return on the stocks of large companies and the 3-month Treasury bill rate from the secondary market[2]. The total return on the stocks of large companies is taken from the Ibbotson Associates 1998 Annual Statistical Yearbook, and the 3-month Treasury bill rate is extracted from the Datastream database.

The sample period that we consider consists of 312 monthly observations from January 1971 to December 1996 for the following variables:

Excess Returns (ER) is the difference between the total return on the stocks of large companies and the 3-month Treasury bill rate from the secondary market. The total return on the stocks of large companies is taken from the Ibbotson Associates 1998 Annual Statistical Yearbook, and the 3-month Treasury bill rate is extracted from the Datastream database.

The sample period that we consider consists of 312 monthly observations from January 1971 to December 1996 for the following variables: Excess Returns (ER) is the difference between the total return on the stocks of large companies and the 3-month Treasury bill rate from the secondary market. The total return on the stocks of large companies is taken from the Ibbotson Associates 1998 Annual Statistical Yearbook, and the 3-month Treasury bill rate is extracted from the Datastream database.

ER will be our dependent variable in various APT models, and we next identify a group of independent variables that could be significant risk factors for stocks. The variable TERM is an interest rate spread between the 10-year Treasury bond yield and the 3-month Treasury bill rate[3]. The interest rate spread variable TERM measures forward interest rates and decreases near peaks of economic activity and increases near economic downturns. According to Jensen *et al*. (1996) this relation exists because short rates generally rise more than long rates in an expanding economy, and fall further during contractions. Expected returns on bonds vary with the term premium; stock returns and term premiums exhibit a similar variation (Fama and French, 1989). As a result, TERM is used as a measure of the term premium or term risk. To the extent that TERM does increase near economic downturns, we would expect this to be a positive risk factor that would increase the required equity premium for stocks as the general economy becomes riskier.

As our measure of interest rates, we use the first difference of the 10-year Treasury bond yield (BOND). The first difference of bond yields, rather than the level of interest rates, is used for two specific reasons. First, the first difference of bond yields can be used as a proxy for the innovation in the interest rate as demonstrated by Sweeny and Warga (1986). Secondly, we conduct augmented Dickey-Fuller unit root tests and find that the 10-year interest rate is not a stationary series, but we find that the first difference of interest rates is stationary.

We use the first difference of Bernake and Mihov's quantitative index as our measure of monetary policy (POLICY) to capture the monthly innovations in

[2] Elyasiani and Mansur (1998) calculate a similar measure of excess returns for banks using the one-year Treasury bill rate.
[3] The data are from the Datastream database.

monetary policy[4]. Unit root tests also confirm that the first difference of the policy index is stationary, while the level of that series has a unit root. In addition to the three basic variables that we consider as risk factors (TERM, BOND and POLICY), we also want to investigate the potential effects of monetary policy uncertainty and interest rate uncertainty to determine whether the second moments of certain risk factors (BOND and POLICY) influence stock returns. Further, we consider whether the variability of stock returns measured by the conditional variance of returns has a significant effect on the conditional mean of stocks, i.e., whether we can confirm a positive risk-return tradeoff for excess stock returns.

C. *APT Model Specification*

In this section, we outline several APT models to relate excess returns (ER) on stocks to six possible risk factors: term structure risk (TERM), interest rate risk (BOND), monetary policy risk (POLICY), monetary policy uncertainty risk (conditional variance of policy: CVPOLICY) and interest rate uncertainty risk (conditional variance of interest rates: CVBOND), and stock return variability. We start by considering the following base APT-GARCH(1,1) model of the first three basic risk factors described above:

$$\mathrm{ER}_t = \beta_0 + \sum_{i=1}^{a} \beta_i \mathrm{ER}_{t-i} + \beta_{n+1}\mathrm{TERM}_t + \beta_{n+2}\mathrm{POLICY}_t + \beta_{n+3}\mathrm{BOND}_t + \epsilon_t \quad (2)$$

$$\sigma^2_{\epsilon t} = \alpha_0 + \alpha_1 \epsilon^2_{t-1} \quad (3)$$

Equation (2) above describes the conditional mean of Excess Returns (ER) as a function of some optimal number of autoregressive lags of Excess Returns, TERM, POLICY and BOND. Equation (3) describes the conditional variance of ER, which is assumed to follow a GARCH(1,1) specification. After first considering the empirical results of an APT model with the three basic risk factors for the first moments, we next investigate the addition of various risk factors that allow the second moments of a risk factor to impact stock returns.

D. *Empirical Results for the First Moments*

An inspection of the correlogram for ER and the residuals from various model specifications indicates that the optimal number of autoregressive terms for the conditional mean of ER in Equation (1) is three, and Table 1 displays the results of the first APT-GARCH(1,1) model. All three autoregressive terms and all three risk factors (TERM, POLICY and BOND) are statistically significant at the 1% level for all variables except the first autoregressive lag, which is significant at the 5% level. The Q(12) and Q^2 (12) diagnostic test-statistics indicate that the residuals and squared residuals are serially uncorrelated. The GARCH term α_2 is large (close to one) and statistically significant, indicating a high degree of persistence in the conditional variability of stock returns. Further, the estimated coefficients for α_1 and α_2 in the conditional variance are both positive and sum to less than one, indicating that the conditional variance of ER is stationary[5].

TERM and POLICY are both positive and significant at the 1% level in Table 1, indicating that those variables are priced by the stock market as positive risk factors, which increases the risk premium on stocks. We speculate that as the economy begins to enter a recessionary period, there is a move toward more expansionary monetary policy, which is captured in our POLICY variable. Monetary expansion would also tend to lower short-term interest rates and increase the forward premium measured in our TERM variable. Therefore, when economic contractions are counteracted with lower short-term interest rates and monetary expansion, it is a signal to the stock market that the economy in general has become more risky, and that risk is priced as an increasing risk premium for stocks. This interpretation is also consistent with Romer and Romer's finding that the Federal Reserve possesses a statistically significant and quantitatively important information advantage about the future state of the economy, and the Fed's policy actions provide direct signals of that information.

[4] The data for the monetary policy index was kindly supplied by Illian Mihov.
[5] Specifications other than GARCH(1,1) are estimated for the conditional variance, but we find a GARCH(1,1) model to be the best.

In addition, we find that the variable BOND is significantly negative ($t - \text{stat} = 3.88$), indicating that changes in interest rates are inversely related to excess stock returns. Several explanations may account for this relationship. First, firms are net debtors and when interest rates fall (rise), the overall cost of debt declines (increases), increasing (decreasing) profits, and increasing (decreasing) stock returns relative to a risk-free asset. Secondly, lower (higher) interest rates mean that the rate used to discount a firm's future earnings declines (increases), raising (lowering) stock prices and stock returns. Finally, since real interest rates are generally considered to be procyclical, lower (higher) interest rates during a contracting (expanding) and more (less) risky economy would raise (lower) the equity risk premium.

After establishing that there are three significant risk factors in the level (TERM) or first difference (BOND and POLICY) of these variables, we next investigate empirically whether equity markets price uncertainty as a risk factor. Specifically, we consider whether, and to what extent, the second moments of the variables BOND and POLICY affect the market risk premium for stock returns.

E. *Empirical Results for Second Moments*

It is important to first determine whether interest rate uncertainty and policy uncertainty are significantly time-varying. To the extent that uncertainty about changes in either future interest rates or changes in future monetary policy are significant, the conditional variance of either variable should be significantly time-varying. We therefore estimate separate autoregressive OLS models for the conditional means of BOND and POLICY, and these results are displayed in Panels A of Tables 2 and 3. For both variables, we determine that the optimal autoregressive lag length is two, and therefore specify separate AR(2) models for the conditional means of BOND and POLICY. For both models, the diagnostic Q(12) tests presented in Panel A of Tables 2 and 3 indicate no evidence of serially correlated residuals out to 12 lags, but the $Q^2(12)$ test-statistics and the ARCH (4) tests show that the squared residuals are serially correlated. The significant conditional heteroskedasticity present in the residuals indicates that interest rate variability and policy variability are significantly time-varying.

To model the conditional variability, we next estimate separate AR(2)-GARCH(1,1) models of BOND and POLICY, and present these results in Tables 2 and 3, Panel B. Diagnostic tests now show that both the residuals and squared residuals are serially independent, indicating that our AR(2)-GARCH(1,1) is an appropriate model of the conditional mean and conditional variance of the two variables under consideration[6]. From each of the AR(2)-GARCH(1,1) models in Panel B (Tables 2 and 3), we generate and save the conditional variance of each variable (BOND and POLICY) as a time-series measure of the uncertainty of policy and interest rates, respectively.

The two measures of uncertainty (CVPOLICY and CVBOND) are now added as additional risk factors to the APT model outlined in Equation (2), and the new APT-GARCH(1,1) model appears below :

$$\text{ER}_t = \beta_0 + \sum_{i=1}^{3} \beta_i \,\text{ER}_{t-i} + \beta_4 \,\text{TERM}_t + \beta_5 \,\text{POLICY}_t + \beta_6 \,\text{BOND}_t + \beta_7 \,\text{CVPOLICY}_t + \beta_8 \,\text{CVBOND}_t + \epsilon_t \tag{4}$$

$$\sigma^2_{\epsilon t} = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \alpha_2 \sigma^2_{\epsilon t-1} \tag{5}$$

Equations (4) and (5) are jointly estimated and the results are displayed in Table 4. All three original risk factors (TERM, POLICY and BOND) are still significant at the 1% level with the same signs as in Table 1, and coefficients for the three autoregressive lags of ER are almost identical to those in Table 1. The Q-tests in Table 4 reveal that there is no pattern in either the residuals or the squared residuals. The uncertainty variable CVBOND is negative and statistically significant (1% level, $t - \text{statistic} = -3.53$), suggesting that interest rate variability is inversely related to stock returns. As interest rates become more volatile, bonds become more risky to hold as an asset relative to stocks, resulting in a lower required risk premium for equities. The variable CVPOLICY is not significant, indicating that monetary policy uncertainty is not a risk factor that gets priced in equity markets.

[6] For each variable, the GARCH coefficients sum to less than one, a condition for the variance to be stationary.

POLICY is priced as a significant risk factor, meaning that U.S. equity markets consider the current effects of monetary policy when valuing stocks, but uncertainty about future monetary policy does not appear to be a significant risk factor.

We next extend our empirical analysis in several directions. The results presented in Table 4 testing for the possible effects of uncertainty on stock returns involve a two-step estimation process, where the conditional variances of interest rates and monetary policy are first generated from the equations presented in Tables 2 and 3 (Panels B), and then allowed to appear as regressors in a subsequent estimation reported in Table 4. It is well known that a two-stage process of generating regressors for use in a subsequent model results in a loss of efficiency and consistency in estimation, compared to a simultaneous estimation procedure. To overcome this potential loss of efficiency, we next construct a statistical APT bivariate GARCH-M model to simultaneously estimate excess returns and monetary policy uncertainty (or interest rate uncertainty) in a system of equations. A bivariate GARCH-M model allows for the joint estimation of the conditional means, conditional variances, and covariances of Excess Returns (ER) and monetary policy (POLICY) and is presented here:

$$\mathrm{ER}_t = \beta_0 + \sum_{i=1}^{3} \beta_i \mathrm{ER}_{t-i}\, \beta_4 \mathrm{BOND}_t + \beta_5 \mathrm{TERM}_t + \beta_6 \mathrm{POLICY}_t + \beta_7 \sigma^2_{vt} + \beta_8 \sigma^2_{\epsilon t} + \epsilon_t \tag{6}$$

$$\sigma^2_{\epsilon t} = \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \alpha_2 \sigma^2_{\epsilon t-1} \tag{7}$$

$$\mathrm{POLICY}_t = \Theta_0 + \Theta_1 \mathrm{POLICY}_{t-1} + \Theta_2 \mathrm{POLICY}_{t-2} + v_t \tag{8}$$

$$\sigma^2_{vt} = \alpha_3 + \alpha_4 v^2_{t-1} + \alpha_5 \sigma^2_{vt-1} \tag{9}$$

$$\mathrm{COV}_t = \rho_{\epsilon v} \sigma_{\epsilon t} \sigma_{vt} \tag{10}$$

Like before in Equations (2) and (4), Equation (6) describes the conditional mean of Excess Returns (ER) as function of three autoregressive lags and three risk factors: BOND, TERM, and POLICY, and Equation (8) is an AR(2) representation of the conditional mean of monetary policy (POLICY). Equations (7) and (9) are GARCH(1,1) representations of the conditional variances of ER and POLICY, respectively. Finally, Equation (10) is the constant conditional correlation model of the covariance between equations, i.e., between ϵ_t and v_t.

An advantage of this GARCH(1,1)-M system of equations is that both conditional means (ER and POLICY) are jointly estimated, along with the conditional variances of each variable ($\sigma^2_{\epsilon t}$ and σ^2_{vt}) and the conditional variances are allowed to appear as regressors in either conditional mean equation. Therefore, we can simultaneously generate an estimate the conditional variance of POLICY (σ^2_{vt}) in Equation (9), and allow that measure of policy uncertainty to affect the conditional mean of ER in equation (6). If monetary policy uncertainty is an important risk factor, the estimated coefficient β_7 in equation (6) will be statistically significant.

A further advantage of the GARCH(1,1)-M specification is that it also allows the conditional variance of ER ($\sigma^2_{,t}$) to appear in its own conditional mean Equation (6). This allows us to statistically test whether the variability of excess stock returns affects the conditional mean of stock returns. We would expect that the increased volatility of stock returns would generally make stock more risky, increasing excess returns and the risk premium ER. To the extent that there is an expected risk-return relationship between conditional excess returns and the conditional variance of returns, the estimated coefficient β_8 should be positive and significant in Equation (6).

Table 5 reports the maximum-likelihood estimates of the GARCH(1,1)-M system described above in Equations (6) – (10)[7]. To test for any patterns in the residuals, Ljung-Box Q statistics are calculated at 12 lags for the levels, squares and cross-products of the residuals and these are reported at the bottom of Table 5. These diagnostic Q-tests indicate that there is no serial correlation in the residuals or squared residuals of Equations (6) or (8) and no serial correlation in the cross-products of the residuals in Equation (10). Further,

[7] The multivariate GARCH-M systems of equations are estimated using the MGARCH software program available from the University of California-San Diego.

the GARCH (1,1) terms in both conditional variance equations (5) and (7) are all statistically significant at the 1% level, and in both cases the condition of a stationary variance is met, i.e., the sum of the GARCH coefficients is less than one.

In Table 5, the estimated coefficients in the bivariate GARCH-M system for the autoregressive lags in the conditional mean equations and the GARCH coefficients for both ER and POLICY are similar to previous results in Tables 1 and 2. The three risk factors (TERM, BOND and POLICY) are all still statistically significant at the 1% level, with the same signs as before. Parallel to the results reported in Table 4, the conditional variance of monetary policy (σ^2_{vt}) is positive but statistically insignificant, indicating that uncertainty about monetary policy is not a significant risk factor for stock returns. We do find a significantly positive relationship (1% level) between the conditional variance of stock returns (estimated coefficient for $\sigma^2_{\epsilon t}$ is .68, $t-$ statistic $=$ 2.70) and the conditional mean of excess returns, confirming the expected risk-return tradeoff for stocks.

To next determine whether interest rate volatility is still a significant risk factor using a bivariate GARCH-M approach, we estimate a new system of equations similar to Equations (6)-(10), but substitute an AR(2) equation for the conditional mean of interest rates (BOND) in Equation (8) for the previous POLICY equation. Equation (9) now becomes the equation for the conditional variance of interest rates (BOND), and this estimated measure of interest rate volatility (σ^2_{vt}) appears as a regressor in the equation for the conditional mean of excess returns (ER). The conditional variance of excess stock market returns ($\sigma^2_{\epsilon t}$) is also allowed to affect the conditional mean of excess returns, to again test for the risk-return tradeoff.

In Table 6, the maximum likelihood estimates of the multivariate GARCH(1,1)-M system of the five equations (6) – (10) are displayed. The Ljung-Box Q-statistics for the levels, squares, and cross-equation products of the standardized residuals show that the time series model for the conditional means and conditional variances of ER and BOND adequately captures the joint distribution of the residuals. All three original risk factors (BOND, TERM, POLICY) remain significant at the 5% level or higher. Our key result is that the estimated coefficient for interest rate volatility (σ^2_{vt}) is negative ($-$.008) and significant ($t-$ statistic $=$ 2.83) at the 1% level, confirming our previous finding that interest rate volatility lowers the risk premium for stocks. As bond returns become more variable, the risk premium for holding stocks declines. Further, when the conditional variance of ER ($\sigma^2_{\epsilon t}$) is allowed to affect the conditional mean of ER, its coefficient is positive (.81) and significant (t = 2.95) at the 1% level. As stock returns become more variable, the risk premium increases.

Conclusion and Summary

This paper investigates the impact of monetary policy shocks on stock returns using a multi-factor Arbitrage Pricing Theory framework that also considers other potential risk factors including interest rates, forward rates, and the volatility of interest rates and monetary policy. Our key empirical result indicates that changes in Bernanke and Mihov (1998) monetary policy index is a positive risk factor that significantly affects excess returns for monthly U.S. stocks over the 1971-1996 period. We argue that this relationship is due to the signal to financial markets that changes in monetary policy reveal about the Federal Reserve's forecast of future economic activity, consistent with the findings of Romer and Romer, and Peek, Rosengren and Tootell, that the Fed actually does possess inside information that is not known to the public[8]. We argue that this central bank information signaling explanation is fully consistent with recent work by (Vassalou, 2003, forthcoming) who shows that news about future economic activity (GDP) significantly explains variations in stock market returns. It is also fully inconsistent with the view that it reflects a positive real effect of monetary policy changes. Such a positive effect would lower rather than raise the equity risk premium.

[8] Romer and Romer (2000) argue that the Federal Reserve has an information advantage over the public because of the vast resources it is able to devote to gathering economic data and forecasting, not because of any inside knowledge about monetary policy or early access to government data. In contrast, Peek, Rosengren and Tootell (2003) argue that the specific source of the Fed's informational superiority is its confidential bank supervisory knowledge about troubled, non-publicly traded institutions.

In addition, we find that increases in long-term (10-year Treasury bond) interest rates significantly lower excess stock returns. This is consistent with Elyasiani and Mansur (1998) findings for excess bank returns, and with the view changes in long-term real interest rates provide market participants with procyclical indications about future economic conditions. Similar reasoning also explains why increases in the term premium (forward rates) are positively and significantly related to excess returns.

Lastly, we investigate the possible effects of interest rate and monetary policy volatility on excess stock returns using various GARCH methods. GARCH models provide a unique statistical framework to test whether volatility is a significant factor in the determination of risk premia for stocks. Using both single equation GARCH models and a multivariate GARCH-M system of equations, we find that the second moment of the 10-year bond interest rate is negatively and significantly related to excess stock returns. Since increased interest rate volatility increases the riskiness of holding bonds, the premium needed by equity holders should then be expected to decrease. In addition, our GARCH-M system shows that the conditional variance of excess returns is positively related to its own conditional mean. The finding of a positive risk-return frontier confirms previous findings in the literature (see French *et al*., 1987). On the other hand, we find that although monetary policy is directly related to stock returns through an information signaling channel, the variability of monetary policy is not priced as a significant risk factor.

The major conclusions drawn from our paper are that: 1) the Fed has inside information about the economy that is not known to the public, 2) statistically significant information about the future direction of the economy is revealed by changes in monetary policy, and 3) current changes in monetary policy are priced as a positive risk factor by the stock market. Taken together, this supports the view that the transmission mechanism of monetary policy is through a wealth effect channel, where information signaling by the Fed induces changes in asset prices.

References

Bernanke, B. S. (1986). Alternative Explanations of the Money-Income Correlation, *National Bureau of Economic Research Working Paper*: 1842.

Bernanke, B. S. and Blinder, A. S. (1992). The Federal Funds Rate and the Channels of Monetary Transmission, *American Economic Review* 82, 901–921.

Bernanke, B. S. and Mihov, I. (1998). Measuring Monetary Policy, *Quarterly Journal of Economics* 113, 869–902.

Black, F. (1993). Banking and Interest Rates in a World Without Money, *Free Banking, Volume 3: Modern Theory and Policy*, 168–79; Brookfield, Vermont: Ashgate.

Blanchard, O. J. and Watson, M. W. (1986). Are Business Cycles All Alike?, *National Bureau of Economic Research Studies in Business Cycles* Vol. 25, Chicago and London: University of Chicago Press.

Boschen, J. F. and Mills, L. O. (1991). The Effects of Countercyclical Monetary Policy on Money and Interest Rates: An Evaluation of Evidence from FOMC Documents, *Federal Reserve Bank of Philadelphia Research Working Paper*: 91–20.

Chami, R., Cosimano, T. F., and Fullenkamp, C. (1999). The Stock Market Channel of Monetary Policy, International Monetary Fund Working Paper.

Christiano, L. J. and Eichenbaum, M. (1992). Liquidity Effects, the Monetary Transmission Mechanism, and Monetary Policy, *Federal Reserve Bank of Chicago Economic Perspectives* 16, 2–14.

Christiano, L. J., Eichenbaum, M., Evans. M., and Evans, C. (1994). The Effects of Monetary Policy Shocks: Some Evidence From the Flow of Funds, *Review of Economics and Statistics* 78, 16–34.

Elyasiani, E. and Mansur, I. (1998). Sensitivity of the Bank Stock Returns Distribution to Changes in the Level and Volatility of Interest Rate: A GARCH-M Model, *Journal of Banking and Finance* 22, 535–63.

Fama, E. F. and French, K. R. (1989). Business Conditions and Expected Returns on Stocks and Bonds, *Journal of Financial Economics* 25, 23–49.

French, K.R., Schwert, G.W., and Stambaugh, R. F. (1987). Expected Stock Returns and Volatility, *Journal of Financial Economics* 19, 3–29.

Friedman, B. M. and Kuttner, K. N. (1992). Money, Income, Prices, and Interest Rates, *American Economic Review* 82, 472–492.

Hoover, K. D. and Perez, S. J. (1994). Post Hoc Ergo Propter Once More: An Evaluation of ”Does Monetary Policy Matter?” in the Spirit of James Tobin, *Journal of Monetary Economics* 34, 47–73.

Jensen, G. R., Mercer, J. M. and Johnson, R. R. (1996). Business Conditions, Monetary Policy, and Expected Security Returns, *Journal of Financial Economics* 40, 213–37.

Kuttner, N., and Mosser. P. C. (2002). The Monetary Transmission Mechanism: Some Answers and Further Questions, *Federal Reserve Bank of New York Economic Review* 8, 15–24.

Lastrapes, W. D. (1998). International Evidence on Equity Prices, Interest Rates and Money, *Journal of International Money and Finance* 17, 377–406.

McCallum, B. T. (1983). A Reconsideration of Sims' Evidence Concerning Monetarism, *Economics Letters* 13, 167–171.

Mishkin, F. S. (1995). Symposium on the Monetary Transmission Mechanism, *Journal of Economic Perspectives* 9, 3–10.

Patelis, A. D. (1997). Stock Return Predictability and the Role of Monetary Policy, *Journal of Finance* 52, 1951–72.

Peek, J., Rosengren, E., and Tootell, M. B. (2003). Does the Federal Reserve Possess an Exploitable Informational Advantage?, *Journal of Monetary Economics* 50, 817–839.

Romer, C. D. and Romer, D. H. (1989). Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz, *NBER macroeconomics annual*: 1989 Cambridge, Massachusetts and London: MIT Press.

Romer, C. D. and Romer D. H. (2000). Federal Reserve Information and the Behavior of Interest Rates, *American Economic Review* 90, 429–457.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing, *Journal of Economic Theory* 13, 341–60.

Rozeff, M. S. (1974). Money and Stock Prices: Market Efficiency and the Lag in Effect of Monetary Policy, *Journal of Financial Economics* 1, 245–302.

Sims, C. A. (1986). Are Forecasting Models Usable for Policy Analysis?, *Federal Reserve Bank of Minneapolis Quarterly Review* 10, 2–16.

Sweeney, R. J. and Warga, A. (1986). The Pricing of Interest-Rate Risk: Evidence from the Stock Market, *Journal of Finance* 41, 393–410.

Thorbecke, W. (1997). On Stock Market Returns and Monetary Policy, *Journal of Finance* 52, 635–54.

Vassalou, M. (2003) (forthcoming). News Related to Future GDP Growth as a Risk Factor in Equity Premiums, *Journal of Financial Economics*.

Table 1
APT GARCH(1,1) MODEL OF EXCESS RETURNS

Variable	Coefficient	t-statistic
Constant	−4.19	-5.92^{***}
ER_{t-1}	0.14	2.49^{**}
ER_{t-2}	0.17	2.17^{***}
ER_{t-3}	0.16	2.99^{***}
TERM	0.81	4.30^{***}
POLICY	95.77	4.80^{***}
BOND	−31.86	-3.88^{***}
α_0	1.42	1.62
α_1	.05	1.37
α_2	.87	13.55^{***}
Diagnostic Tests		
Q(12)	17.58	–
$Q^2(12)$	8.64	–
R^2	0.315	–

Dependent variable is Excess Returns (Stock Return - 3 month T-bill). *** indicates statistical significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level. Q(12) are the Ljung-Box statistics for twelfth-order serial correlation in the residuals and Q2(12) are the Ljung-Box statistics for twelfth-order serial correlation in the squared residuals. The critical value at the 0.05 significance level is 21.02 for 12 degrees of freedom. Sample period is monthly from 1971.01 to 1996.12.

Table 2
OLS and GARCH(1,1) MODELS OF POLICY

	A. OLS MODEL		B. GARCH(1,1) MODEL	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-0.0001	-0.27^{***}	-0.0001	-1.75^{*}
POLICY_{t-1}	0.53	9.55^{***}	0.47	7.75^{***}
POLICY_{t-2}	-0.22	-4.13^{***}	0.17	2.70^{***}
α_0	–	–	0.0001	2.67^{***}
α_1	–	–	0.27	4.82^{***}
α_2	–	–	0.70	14.88^{***}
Diagnostic Tests				
Q(12)	14.32		18.47	
$Q^2(12)$	209.34^{***}		12.59	
ARCH(4)	60.38^{***}		1.17	
Log Likelihood	1001.4		1120.1	

Dependent variable is POLICY. *** indicates statistical significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level. Q(12) are the Ljung-Box statistics for twelfth-order serial correlation in the residuals and Q(2)(12) are the Ljung-Box statistics for twelfth-order serial correlation in the squared residuals. The critical value at the 0.05 significance level is 21.02 for 12 degrees of freedom. Sample period is monthly from 1971.01 to 1996.12.

Table 3
OLS and GARCH(1,1) MODELS OF BOND

	A. OLS MODEL		B. GARCH(1,1) MODEL	
Variable	Coefficient	t-statistic	Coefficient	t-statistic
Constant	0.0007	0.48	0.001	1.24
$BOND_{t-1}$	0.39	8.63^{***}	0.37	7.17^{***}
$BOND_{t-2}$	−0.20	-4.44^{***}	−0.14	2.98^{***}
α_0	–	–	0.0001	1.98^{**}
α_1	–	–	0.08	4.84^{***}
α_2	–	–	0.84	14.95^{***}
Diagnostic Tests				
Q(12)	14.48		13.93	
$Q^2(12)$	26.12^{**}		10.19	
ARCH(4)	5.54^{***}		1.66	
Log Likelihood	952.0		977.2	

Dependent variable is BOND. *** indicates statistical significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level. Q(12) are the Ljung-Box statistics for twelfth-order serial correlation in the residuals and $Q^2(12)$ are the Ljung-Box statistics for twelfth-order serial correlation in the squared residuals. The critical value at the 0.05 significance level is 21.02 for 12 degrees of freedom. Sample period is monthly from 1971.01 to 1996.12.

Table 4
APT GARCH(1,1) MODEL OF EXCESS RETURNS WITH UNCERTAINTY

Variable	Coefficient	t-statistic
Constant	−1.83	−1.89*
ER_{t-1}	0.12	1.92*
ER_{t-2}	0.17	2.83***
ER_{t-3}	0.16	3.01***
TERM	0.85	4.40***
POLICY	99.84	4.64***
BOND	−31.58	−3.96***
CVBOND	**−24.58**	**−3.53*****
CVPOLICY	**12.48**	**0.96**
α_0	1.92	1.50
α_1	0.07	1.42
α_2	0.81	8.12***
Diagnostic Tests		
Q(12)	14.98	
$Q^2(12)$	10.84	
R^2	.335	

Dependent variable is Excess Returns (Stock Return - 3 month T-bill). *** indicated statistical significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level. Q(12) are the Ljung-Box statisticx for twelfth-order serial correlation in the residuals and $Q^2(12)$ are the Ljung-Box statistics for twelfth-order serial correlation in the squared residuals. The critical value at the 0.05 significance level is 21.02 for 12 degrees of freedom. Sample period is monthly from 1971.01 to 1996.12.

Table 5
Bivariate GARCH(1,1)-M Model for POLICY - Constant Conditional Correlations

(6) $$ER_t = \underset{(1.57)}{-1.79} + \underset{(1.46)}{.09}\,ER_{t-1} + \underset{(2.14)}{.14}\,ER_{t-2} + \underset{(3.04)}{.16}\,ER_{t-3} + \underset{(4.99)}{38.11}\,BOND_t + \underset{(4.39)}{.87}\,TERM_t$$
$$+ \underset{(5.60)}{145.32}\,POLICY_t + \underset{\mathbf{(0.98)}}{\mathbf{20.21}}\boldsymbol{\sigma^2_{vt}} + \underset{\mathbf{(2.70)}}{\mathbf{.68}}\boldsymbol{\sigma^2_{\in t}} + \in_t$$

(7) $$\sigma^2_{\in t} = \underset{(0.83)}{.24} + \underset{(3.01)}{.10}\,\in^2_{t-1} + \underset{(27.80)}{.89}\sigma^2_{\in t-1}$$

(8) $$POLICY_t = \underset{(1.61)}{-.001} + \underset{(7.63)}{.47}\,POLICY_{t-1} - \underset{(2.64)}{.17}\,POLICY_{t-2} + v_t$$

(9) $$\sigma^2_{vt} = \underset{(0.83)}{.0001} + \underset{(5.09)}{.30}\,v^2_{t-1} + \underset{(16.17)}{.69}\sigma^2_{vt-1}$$

(10) $$COV_t = \underset{(2.18)}{-.17}\sigma_{\in t}\sigma_{vt}$$

	ER Eqn.	POLICY Eqn.	Cross-Eqn.
Q(12)	11.49	17.41	8.17
$Q^2(12)$	9.77	10.76	–

Log Likelihood Function = 230.35

Absolute values of t-statistics are in parentheses. Q(12) is the Ljung-Box statistic for twelfth-order serial correlation in the residuals and $Q^2(12)$ is the Ljung-Box statistic for twelfth-order serial correlation in the squared residuals. The critical value at the 5% significance level is 21.02 for 12 degrees of freedom. Sample is 312 monthly observations from January 1971 to December 1996.

Table 6
Bivariate GARCH(1,1)-M Model for TBONDS - Constant Conditional Correlations

$$(11)\quad ER_t = \underset{(1.81)}{-2.48} + \underset{(1.83)}{.11}\,ER_{t-1} + \underset{(2.20)}{.13}\,ER_{t-2} + \underset{(2.80)}{.14}\,ER_{t-3} - \underset{(2.18)}{25.85}\,BOND_t + \underset{(5.32)}{.92}\,TERM_t + \underset{(5.16)}{97.29}\,POLICY_t$$

$$+ \underset{(\mathbf{2.83})}{\mathbf{.008}}\sigma^{\mathbf{2}}_{\mathbf{vt}} + \underset{(\mathbf{2.95})}{\mathbf{.81}}\sigma^{\mathbf{2}}_{\in \mathbf{t}} + \in_t$$

$$(12)\quad \sigma^2_{\in t} = \underset{(1.23)}{.47} + \underset{(2.92)}{.09}\in^2_{t-1} + \underset{(25.54)}{.88}\sigma^2_{\in t-1}$$

$$(13)\quad BOND_t = \underset{(0.94)}{-.013} + \underset{(7.45)}{.46}\,BOND_{t-2} - \underset{(3.54)}{.22}\,BOND_{t-3} + v_t$$

$$(14)\quad \sigma^2_{vt} = \underset{(1.26)}{.0006} + \underset{(2.92)}{.11}\,v^2_{t-1} + \underset{(13.08)}{.83}\sigma^2_{vt-1}$$

$$(15)\quad COV_t = \underset{(0.55)}{-.065}\sigma_{\in t}\sigma_{vt}$$

	ER Eqn.	BOND Eqn.	Cross-Eqn.
Q(12)	18.28	14.94	3.50
$Q^2(12)$	12.25	10.55	–

Log Likelihood Function = 261.18

Absolute values of t-statistics are in parentheses. Q(12) is the Ljung-Box statistic for twelfth-order serial correlation in the residuals and $Q^2(12)$ is the Ljung-Box statistic for twelfth-order serial correlation in the squared residuals. The critical value at the 5% significance level is 21.02 for 12 degrees of freedom. Sample is 312 monthly observations from January 1971 to December 1996.

ABOUT THE AUTHORS

Tony Caporale is Professor of Economics at Ohio University. He received his Ph.D. in Economics from George Mason University in 1992 and his BA in economics from New York University in 1986. His research areas of specialization are macroeconomics, monetary economics and political economy. His teaching interests include macroeconomics, econometrics, and the economics of sports.

Mark J. Perry is Professor of Finance and Economics at the University of Michigan-Flint, where he holds a joint appointment in the School of Management and the Department of Economics in the College of Arts and Sciences. Dr. Perry joined the University of Michigan in 1996, and he has taught undergraduate and graduate courses in economics and finance for the Department of Economics, the Masters of Public Administration Program, and the School of Management. In 1999, he was a visiting professor at the Togliatti Academy of Management in Togliatti, Russia, and in 2005 he was a visiting professor at the Alliance Business Academy in Bangalore, India.

Dr. Perry received his MBA degree in finance from the Carlson School of Management at the University of Minnesota, and then received masters and doctoral degrees in economics from George Mason University in Washington, D.C. His primary academic research is in the area of financial economics, and he has published several dozen scholarly articles and book chapters in peer-reviewed finance and economics journals.