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Stock Return Predictability and The Role of Monetary Policy

ALEX D. PATELIS*

ABSTRACT

This article examines whether shifts in the stance of monetary policy can account for the observed predictability in excess stock returns. Using long-horizon regressions and short-horizon vector autoregressions, the article concludes that monetary policy variables are significant predictors of future returns, although they cannot fully account for observed stock return predictability. I undertake variance decompositions to investigate how monetary policy affects the individual components of excess returns (risk-free discount rates, risk premia, or cash flows).

THIS ARTICLE EXAMINES THE forecasting power of monetary policy variables in nested regressions with the financial variables used in the stock predictability literature. It seeks to establish whether there is marginally significant forecasting power in either set. The empirical method followed initially uses the same long-horizon regressions as Fama and French (1989). An alternative strategy to long-horizon regressions used in this article is that of inferring the long-term behavior of expected returns from short-horizon vector autoregressions (VARs) (see Campbell (1991) and Campbell and Shiller (1988b)). I also undertake return variance decompositions to examine the relative importance of the various forecasting variables in causing unexpected stock returns.

Over the past twenty years there has been mounting evidence in the finance literature that speaks against the constant expected returns hypothesis. Whether this has been in the form of variance tests (Shiller (1981)), long-horizon regressions (Fama and French (1989, 1988)), variance ratios (Poterba and Summers (1988)), contrarian strategies (Debondt and Thaler (1985) and Lo and MacKinlay (1990)), short-horizon vector autoregressions (Campbell and Shiller (1988a, 1988b) Campbell (1991)), or any of the many other approaches employed by researchers, the general conclusion is that expected stock returns are time-varying, i.e., that asset returns are, to some extent, predictable.

Because previous research efforts have focused mainly on uncovering empirical evidence against the return unpredictability hypothesis, researchers often have not attempted to interpret their results. In a way, interpretation has not been needed: In order to disprove the constant expected returns hypothesis, a researcher has only to show that a variable contained in a time t information set can help predict asset returns at time $t + k$. It has not

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mattered whether this variable is a financial variable, such as an interest rate spread (e.g., Fama and French (1989)), or a (presumably) unrelated variable, such as the weather conditions in some part of the world (Saunders (1993)).

However, to build a theoretical model of expected asset return behavior, it is crucial that we understand the nature, characteristics, and origins of asset return predictability. What are the economic state variables behind the time-series behavior of expected asset returns and risk premia? Most of the variables that researchers found were good predictors of future asset returns can be interpreted theoretically as indicators of the underlying macroeconomy. For example, Estrella and Hardouvelis (1991) study the term structure, a significant predictor of asset returns, as a predictor of real economic activity. Similarly, Harvey (1988) finds that the expected real term structure can help forecast consumption growth. Stambaugh (1988) documents that the term structure of interest rates behaves differently in expansions and contractions. Fama and French (1989) find that the term spread and the dividend yield are predictors of future asset returns. They interpret these variables as reflecting short-term business cycles and long-term business conditions, respectively.

Furthermore, there is closely related work that examines the behavior of expected returns across different stages of the business cycle. Chen (1991) argues that expected excess returns are negatively related to the recent growth of Gross National Product (GNP) and positively related to its future growth. Patelis (1993) finds that expected stock returns are positively correlated with expected macroeconomic conditions.

This article builds on previous work by examining the relation between expected stock returns and monetary policy, which, according to some theorists, represents a leading source of business cycles. It links the macroeconomic literature that interprets interest rate spreads as indicators of monetary policy with the finance literature that uses interest rate spreads to predict stock returns.

There was considerable debate in the late 70s and early 80s on the relative merits of various monetary aggregates. In contrast, in the early 90s researchers focused mostly on interest rate variables and spreads as indicators of monetary policy. For example, Bernanke and Blinder (1992) argue that the federal funds rate is a relatively good indicator of monetary policy shocks because it is sensitive to shocks to the supply of bank reserves. Similarly, Bernanke (1990) argues that the predictive power of spread between the yield on commercial paper and Treasury Bills (T-bills) stems from its ability to proxy for the stance of monetary policy.

These indicators have also been used to debate another long-standing issue among macroeconomists, that is, whether monetary shocks have real effects. A popular approach has been to estimate the VARs of money, output, interest rates, and price levels (see, e.g., Bernanke and Blinder (1992) and Christiano, Eichenbaum, and Evans (1994a, 1994b)). As a reflection of the underlying economy, the inclusion of asset prices in such models would be useful in settling the issue of the effectiveness of monetary policy.¹ After all, assets such as equities are claims on future economic output, so if monetary policy has real economic effects, then shifts in monetary policy should affect stock prices.

Clearly, given all of the above, it is reasonable to hypothesize that variables such as interest rate spreads predict stock returns because they proxy for the stance of monetary policy. This brings us to the aim of this article, which is to examine empirically the part of stock return predictability that can be attributed to monetary policy. Obviously, we cannot expect monetary policy to fully account for the observed asset return predictability. Still, this appears to be a natural starting point in the examination of the source and nature of time-varying expected returns.

Additional motivation comes from reading the popular financial press. Market analysts (including so-called “Fed watchers”) dedicate considerable efforts to studying and predicting the path of interest rates and the future moves of the Federal Reserve. The financial press often interprets asset price movements as reactions to monetary policy shifts. As an illustration, note the following excerpt from the *New York Times* of February 5, 1994, when the Fed tightened monetary policy after an unusually long period of relatively low interest rates:

The Federal Reserve sent an Arctic blast through Wall Street yesterday, chilling the stock and bond markets and raising questions about the future of this year’s remarkable rally in equities . . . Yesterday’s 96-point decline was the largest for the Dow Jones industrial average since Nov. 15, 1991, when it fell 120.31 points. It was the eighth-biggest daily drop ever.

In fact, the months following February 1994 saw considerable financial uncertainty and volatility.

A careful reading will show that there are two separate relations involved here: There is the contemporaneous relation between stock returns and monetary policy (“Arctic blast . . . 96-point decline”), and a lead-lag relationship (“ . . . raising questions about the future of this year’s remarkable rally in equities”). Given that stock prices are weighted averages of the infinite stream of future expected dividends, and assuming rational expectations, stock prices should immediately reflect the real effects of monetary policy the moment these become apparent. That is, there should be no lags, as is the case with output changes. This is what happened on February 4, 1994.

However, this article is *not* interested in studying this contemporaneous relationship. Instead, it examines the empirical fact that a period of turmoil ensued. This means that we are dealing with a separate phenomenon. (Note that this specific NYT excerpt did in fact “predict” the ensuing volatile market, i.e., we are talking about an *expected* effect here). The finding that monetary policy variables are significant in predicting asset returns, which is the focus of this article, is evidence that something additional is going on, namely, that

¹ There is a large body of literature from the late 70s and early 80s that examines the relation between announcements of monetary aggregates and the reaction of interest rates and asset prices. However, this literature is primarily interested in examining whether monetary variables reflect money demand or supply shocks, and the resulting reaction of interest rates, rather than the behavior of asset prices per se.

monetary policy affects some aspect of economic structure that influences asset return expectations.

Jensen, Mercer, and Johnson (1996) examine some of these issues. Jensen *et al.* construct a crude dummy indicator to reflect discount rate changes and add it to monthly and quarterly regressions of security returns on the Fama and French (1989) indicators. They conclude that “. . . the behavior of the business-conditions proxies (used by Fama and French) and their influence on expected security returns is significantly affected by the monetary sector.” My article differs from the Jensen *et al.* approach in that I am primarily interested in longer-horizon predictability² and whether it can be explained by monetary policy alone. Furthermore, I use recently proposed monetary policy indicators, rather than a dummy variable, to model monetary policy.

In another recent article, Thorbecke (1997) finds that monetary policy expansions increase contemporaneous stock returns. Using a multifactor model, Thorbecke also finds that exposure to monetary policy increases an asset's *ex ante* return (similar to Thorbecke and Alami (1992)). As noted above, I am not interested in the contemporaneous relation between monetary policy and stock returns, rather in the relation between monetary shocks and future expected stock returns.

The outline of the article is as follows: Section I describes the data and the variables used. Section II follows the Fama and French (1989) long-run regression methodology. Section III uses the Campbell and Shiller (1988a, 1988b) VAR approach. Section IV motivates the results theoretically, and Section V concludes.

I. Variables and Data

A. Asset Returns

This article focuses on U.S. stock return data, using the monthly NYSE value-weighted excess stock returns from the Center for Research in Securities Prices (CRSP). To obtain excess returns,³ the CRSP one-month T-bill rate is subtracted from the monthly stock return. To facilitate cross-horizon comparisons, returns are expressed on an annual basis at all time horizons.

B. Monetary Policy Indicators

The measures of monetary policy used here are as follows:

FYFF: The federal funds rate. Bernanke and Blinder (1992) argue that this rate is a good indicator of monetary policy actions because it is sensitive to shocks to the supply of bank reserves. Also note Thorbecke and Alami's (1992) conclusion that the federal funds rate is a priced factor in an arbitrage pricing

² After all, stock return predictability is mostly evident at the annual or biennial horizon. Note, for example, that the adjusted R^2 s of the regressions in Section II are 0.084 at the monthly horizon, but 0.441 at the annual horizon.

³ Note that by studying excess returns, we can abstract from price level considerations, since excess returns are the same whether expressed in nominal or real terms (the price term drops out).

theory (APT) model of stock returns (similar results in Thorbecke (1996)). The source for this information is the Citibase tape, variable FYFF.

FFSPR: The spread between the federal funds rate and the yield on the ten-year Treasury note. This is also motivated by Bernanke and Blinder (1992), as well as Bernanke (1990). It is an attempt to control for differences in the levels of inflation. The source of the ten-year Treasury yield is the Citibase tape, variable FYGT10.

DEFAULT: The spread between the yield on six-month commercial paper and six-month T-Bills. This is negatively related to future output and income. Bernanke (1990) argues that this arises because of the spread's ability to proxy for the stance of monetary policy: In the process of tightening monetary policy, the Federal Reserve induces banks to reduce bank loan supply. This forces corporations to substitute commercial paper for bank loans, which increases borrowing costs, reduces investment, and causes an increase in this spread (the "bank lending" channel). The source here is Citibase, variables FYCP and FYGN6.

DNBRD: The quantity of nonborrowed reserves. This indicator is motivated and used by Christiano and Eichenbaum (1991), Eichenbaum and Evans (1995), and Christiano, Eichenbaum, and Evans (1994a, 1994b) to study the effect of monetary policy. Here, I use the first log difference of the FMRNBC series from the Citibase tape, which measures nonborrowed reserves plus extended credit adjusted for changes in reserve requirements.

STRONGIN: This is the portion of nonborrowed reserve growth orthogonal to total reserve growth. In an influential article, Strongin (1995) argues that innovations to total reserves largely reflect the Fed's accommodation of reserve demand shocks, and that the Fed exerts its influence over the reserve markets by altering the mix of borrowed and nonborrowed reserves it supplies to meet current reserve demand. I obtain STRONGIN series by normalizing the Citibase series FMRNBA and FMRAA by a 36-month moving average of total reserves, and then collecting the residuals of a regression of nonborrowed reserves (FMRNBA) on total reserves (FMRAA).

C. Financial Variables

By the term "financial variables" I loosely denote those variables that traditionally predict stock returns. Among the various candidates, I have selected the following:

YIELD: The dividend yield. There are at least two possible explanations as to why a low dividend yield predicts low future stock returns. First, if we accept the possibility of irrational bubbles, then a low dividend yield signals irrationally high stock prices, i.e., a price bubble that eventually bursts, producing low stock returns. This is an interpretation of the dividend yield as a measure of price bubbles.

Second, as Campbell and Shiller (1988a, 1988b) have shown, using a log-linearized accounting identity, and assuming no bubbles, the log dividend yield d_t

– p_t can be expressed as a weighted average of expectations of future dividend growth Δd_{t+1+j} and returns r_{t+1+j} (a “dynamic Gordon dividend model”):

$$d_t - p_t = \text{constant} + E_t \sum_{j=0}^{\infty} \rho^j [-\Delta d_{t+1+j} + r_{t+1+j}] \quad (1)$$

We can see that whatever the sources of stock return predictability, the dividend yield will reflect them. Thus I interpret the predictive power of the dividend yield as a test of model misspecification. It should not be statistically significant if I include all sources of stock return predictability.

I use a measure of the dividend yield that is constructed from the stock return series, with and without dividends, as in Hodrick (1992). I obtain normalized nominal stock price series by setting the stock price equal to one in the first month of the sample period, and recursively setting $P_t = (1 + RX_t) * P_{t-1}$, where RX_t is equal to value-weighted returns without dividends. Then the annualized dividend yield for each month is calculated as:

$$\text{YIELD}_t = \frac{1}{P_{gt}} \sum_{j=0}^{11} (RN_t - RX_t) P_t \prod_{k=1}^j (1 + i_{t-k+1}) \quad (2)$$

where RN_t is equal to value-weighted returns with dividends and i_t is the one-month T-bill rate. P_{gt} is a nominal price level constructed recursively by setting $P_{gt} = (1 + \text{infl}_t) * P_{gt-1}$, where infl_t is the monthly CPI inflation rate. This corresponds to the usual approach followed in the literature that sums up dividends over a period of a year in order to avoid seasonality issues.

TERM: The spread between the yield on the ten-year government bond and the yield on the one-month T-Bill. Spreads among interest rates of various maturities predict returns. Obviously, this measure of the term structure of interest rates is closely related to monetary policy. The question remains, does its predictive power stem solely from its ability to reflect monetary stance? I use data from the Citibase series FYGT10 (ten-year government bond yield) and the one-month T-bill rate from CRSP.

REALR: The one-month real interest rate. This variable is also used in asset predictability research papers. Furthermore, it is a necessary variable for the variance decompositions. It is constructed by subtracting the monthly inflation rate (found by log-differencing the PUNEW variable (seasonally adjusted CPI) from the Citibase tape) from the one-month T-bill rate obtained from CRSP.

I test the variables for unit roots (test results not reported here). Apart from FFFF, the unit root hypothesis is uniformly rejected.⁴

⁴ Note that in the long-horizon regressions, the presence of a unit root does not invalidate standard statistical theory. However, in Section III, I use the first difference of FFFF, denoted DFFFF, since both stock returns and the other variables included in the VAR are by construction stationary.

II. Long-Horizon Regressions

This section uses Fama and French (1989) long-horizon multivariate regressions to examine whether monetary policy variables help predict stock returns at different time horizons. The Fama and French (1989) approach to testing for asset return predictability regresses asset returns at increasing time horizons on variables contained in time t 's information set. We have the following typical specification:

$$e_{t+k,t+1} = a_k + b_k x_t + \varepsilon_{t+k,t+1} \quad (3)$$

where $e_{t+k,t+1} = e_{t+1} + \dots + e_{t+k}$ is the continuously compounded k -period rate of excess return and x_t is the vector of variables contained in the market's information set at time t .

There are enough observations for the monthly and quarterly horizons to estimate these regressions without resorting to overlapping data. However, for the annual and biennial horizons, the degrees of freedom in nonoverlapping regressions become prohibitively limited, thus the use of overlapping data (based on the quarterly series) is unavoidable. This leads to serial correlation in estimated standard errors.

There are two ways to correct for this: I can use asymptotic standard theory, and I can estimate heteroskedasticity and autocorrelation consistent errors using Newey and West methods. These corrections have the advantage of being analytically simple and asymptotically consistent. However, there are serious small sample biases in the resulting test statistics (see Hodrick (1992)).

An alternative approach is to simulate the model and derive Monte Carlo standard errors under the null of no return predictability. This can be done by bootstrapping quarterly excess stock returns and estimating the regressions by using the resulting overlapping annual and biennial simulated series.⁵ Repeating this exercise 1,000 times gives an estimate of the distribution of the coefficients in small samples under the null of constant excess stock returns.

Table I reports regressions of excess stock returns on monetary and financial variables at different time horizons. For each time horizon (monthly, quarterly, annual, and biennial), the table reports the annualized regression coefficients and their heteroskedasticity- and correlation-consistent (Newey-West) marginal significance levels, the regression R^2 and adjusted- R^2 , and the marginal significances of the coefficients from the Monte Carlo simulations. (Note that these apply only to the overlapping regressions, i.e., to the annual and biennial horizons. Note also that for data availability reasons, the sample period extends from January 1962 to November 1994.)

At first, a casual observation establishes the fact that monetary variables are marginally significant predictors of asset returns across different time horizons and candidate variables. A higher federal funds rate, for example,

⁵ I choose bootstrapping, as opposed to assuming normality, because stock returns exhibit excess skewness and kurtosis. However, experimentation with draws from a normal distribution shows that the results are robust to either specification.

Table I

Nested Regressions with Both Monetary and Financial Variables

This table contains the results from a set of multivariate regressions. Excess stock returns at horizons indicated by each row (monthly (M), quarterly (Q), annual (Y), biennial (2Y)) are regressed on one lag of all the column variables. Annualized New York Stock Exchange (NYSE) value-weighted excess stock returns (source: Center for Research in Security Prices (CRSP)) are constructed by subtracting the one-month T-bill rate (source: CRSP) from the monthly stock return. Annual and biennial stock returns are calculated by overlapping quarterly returns. The regressions include the following variables: the federal funds rate (FYFF), the spread between the federal funds rate and the yield on the ten-year Treasury note (FFSPR), the spread between the yield on six-month commercial paper and six-month T-Bills (DEFAULT), the first log difference of nonborrowed reserves (DNBRD), the portion of nonborrowed reserve growth orthogonal to total reserve growth (STRONGIN), the dividend yield (YIELD), the spread between the yields on the ten-year government bond and the one-month T-bill (TERM) and the one-month real interest rate (REALR). Panel A reports the annualized regression coefficients. Panel B reports the marginal significance of the regression coefficients, using Newey-West heteroskedasticity and autocorrelation consistent asymptotic standard errors. Panel C reports the marginal significance of the regression coefficients derived from 1,000 bootstrapping simulations under the null of no return predictability (that is, with excess returns bootstrapped from the quarterly return distribution and cumulated at the annual and biennial horizons). Panel D indicates the marginal significance of accepting a hypothesis that all the coefficients in each group of variables are zero-based on asymptotic or simulated standard errors. The sample period is January 1962 to November 1994. Bold-face numbers are significant at the five percent level.

	FYFF	FFSPR	DEFAULT	STRONGIN	DNBRD	YIELD	TERM	REALR
Panel A: Regression Coefficients								
M	-9.086	14.153	-6.472	1.239	-0.834	25.890	12.317	0.981
Q	-7.260	4.638	-0.669	0.050	-0.002	25.041	4.282	0.973
Y	-4.037	-0.080	9.519	0.542	-0.003	16.057	0.679	0.596
2Y	-1.473	-1.650	9.935	0.300	0.003	8.258	-1.195	0.625
Panel B: Significance Based on Asymptotic Theory								
M	0.000	0.017	0.620	0.323	0.639	0.000	0.009	0.287
Q	0.004	0.490	0.960	0.967	0.887	0.000	0.444	0.152
Y	0.000	0.974	0.022	0.374	0.458	0.000	0.706	0.088
2Y	0.059	0.302	0.000	0.547	0.260	0.000	0.391	0.041
Panel C: Significance Based on Simulations								
Y	0.026	0.936	0.118	0.626	0.408	0.000	0.814	0.336
2Y	0.334	0.482	0.024	0.738	0.266	0.036	0.546	0.244
Panel D: Exclusion Tests								
	All Monetary Variables		All Financial Variables		R^2	Adj- R^2		
	Asymptotics	Simulations	Asymptotics	Simulations				
M	0.002		0.000		0.103	0.084		
Q	0.001		0.000		0.202	0.150		
Y	0.000	0.000	0.000	0.000	0.476	0.441		
2Y	0.000	0.000	0.002	0.022	0.448	0.409		

indicating tighter monetary conditions, predicts lower expected returns over the short run but higher expected short-horizon returns $e_{t+k,t+k+1}$ further in the future (deduced from the fact that the size of the coefficient declines across time). In most cases when using the Monte Carlo standard errors, predictors also remain significant.⁶

The table also includes the marginal significance of exclusion tests for each set (monetary or financial) of variables. The exclusion tests provide even stronger results by strongly rejecting the hypothesis that excess stock returns are unpredictable if we use either the monetary or the financial variables. This is also true under the simulations.

It is clear that no set of variables is driven out by the other: Both financial and monetary variables remain significant in nested regressions. There is predictive power in the financial variables that is independent of the predictive power of the monetary variables, and vice versa. Why is this the case? It could be that monetary policy represents a significant portion of the explanation for asset return predictability—but only a portion, not the whole. It could also be that the particular position of monetary policy is not adequately captured by the monetary variables used in the analysis, thus additional financial variables have additional forecasting power. Finally, perhaps there is something else driving both monetary and financial variables.⁷

The R^2 s and adjusted R^2 s of the regressions are also noteworthy: They rise to 0.443 and 0.405, respectively, for biennial data. This suggests that more than 40 percent of future variability in excess returns can be predicted by using monetary and financial variables. Figure 1 plots expected and actual biennial returns from these nested regressions. Once more, the constant expectations hypothesis is rejected.

Finally, under the interpretation of the dividend yield as a measure of model misspecification, it is clear that the set of variables describing time variance in expected returns is not sufficiently specified. There are still economic or financial state variables not yet uncovered by econometricians or theorists. These variables can help predict future expected returns and dividend growth. Their effect is captured by the strong statistical significance of the dividend yield.

III. Short Horizon VARs: Return Decompositions

A. Introduction

An alternative modeling strategy to the long-horizon regressions imputes long-horizon statistics from short-horizon VARs. This methodology, developed and applied by Campbell and Shiller (1988a, 1989b), Campbell (1991), Camp-

⁶ Note that univariate and multivariate regressions containing only the monetary variables, not reported here, also confirm these results. Similarly, regressions using the Bernanke-Mihov (1995) indicator are also supportive of the predictive power of monetary variables. Results from the author are available upon request.

⁷ In a separate working paper I find that money endogeneity is not the driving force behind these results.

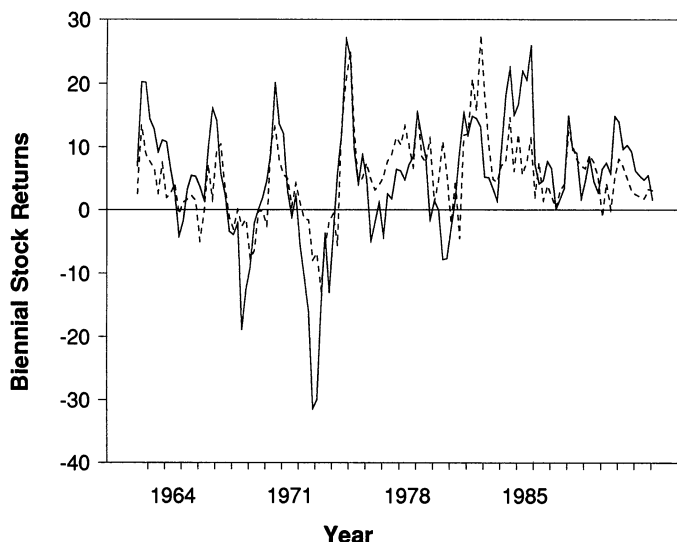


Figure 1. Actual and fitted values from the long-horizon regression. This figure shows actual and fitted biennial NYSE value-weighted excess stock returns obtained from the nested multivariate regressions of Table I from January 1962 to November 1994. Actual, —; fitted, ----.

bell and Ammer (1993), and Campbell and Mei (1993), has the advantage of avoiding the small sample biases inherent in long-horizon, overlapping regressions (see, among others, Hodrick (1992)), and it allows for feedback from stock returns to the forecasting variables.

This section provides alternative estimates of the coefficients of long-horizon Fama and French regressions by using a short-horizon VAR, thus verifying the results of the previous section. I also decompose unexpected stock returns into three components related to future expectations of unexpected returns, real interest rates, and dividend growth. Finally, I examine the portion of the variance of unexpected stock returns that can be attributed to changes in monetary policy conditions, together with the channel through which this operates.

The methodology developed by Campbell and Shiller (1988a, 1988b) and Campbell (1991) to decompose stock returns, is based on two building blocks, a dynamic accounting identity and a one-lag VAR. The accounting identity used is:

$$R_{t+1} = \frac{(P_{t+1} + D_{t+1})}{P_t} - 1 \quad (4)$$

Where P_t is the asset price at time t , D_{t+1} is the dividend paid by the asset in period $t + 1$, and R_t is the return to the asset if held from period t to period $t + 1$. Rearranging for P_t , taking logs, approximating by a first-order Taylor expansion, dropping higher order terms, solving forward, and imposing a

no-bubbles condition, Campbell and Shiller express asset prices at time t in terms of the expectations of future dividends and asset returns:

$$P_t = \text{const} + E_t \sum_{j=0}^{\infty} \rho^j [(1 - \rho)d_{t+1+j} - r_{t+1+j}] \quad (5)$$

where ρ is a constant equal to the ratio of the ex-dividend to the cum-dividend stock prices. (In my sample, ρ is equal to 0.9967 at the monthly horizon and 0.9902 at the quarterly horizon.)

The final step is to take expectations of equation (5), subtract the resulting expression from the original equation, and derive an identity for unexpected excess asset returns:

$$e_{t+1} - E_t e_{t+1} = (E_{t+1} - E_t) \left\{ \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - \sum_{j=1}^{\infty} \rho^j r_{t+1+j} - \sum_{j=1}^{\infty} \rho^j e_{t+1+j} \right\} \quad (6)$$

That is, we can decompose excess asset returns (denoted e) into innovations to dividend growth expectations, to real interest rate (denoted re) expectations, and to excess return expectations.

In addition, since we want to analyze the predictive ability of monetary policy variables, I break the three asset components—dividends, real interest rate, and excess returns—into the parts that can be attributed to each of the forecasting variables. Thus I can infer whether monetary policy innovations are mostly related to changes in future dividend growth expectations (a feature of standard Keynesian models), to changes in real interest rates expectations (again, this is standard Keynesian monetary theory), or to changes in excess return expectations.

Note that real business cycle models predict none of these effects, because they postulate that monetary policy has only nominal effects. Since I am working with real or excess return variables here, real business cycle models do not predict a relation between excess returns and the forecasting variables.

However, I note that a real business cycle theorist might argue that higher inflation leads to higher inflation variance and uncertainty, thus excess returns or real interest rates should be affected. But real business cycle models leave no real role for monetary policy. Any real effect, whether in terms of means or variances or covariances, automatically admits that monetary policy has real effects, whether these work through dividend growth, real interest rates, or asset return riskiness.

The second building block of the Campbell VAR framework is the VAR itself. First, I stack all variables that help measure or forecast excess returns into a vector, z_t . For reasons of parsimony, these include excess stock returns (EVW), real interest rate (REALR), dividend yield (YIELD), term spread (TERM), federal funds rate growth (DFYFF), and the STRONGIN indicator. (Here I follow Campbell and Ammer (1993) in not directly using dividend growth as a

variable, but instead inferring it as a residual. Thus I avoid seasonality problems in constructing a dividend growth series.) Note that all the variables are demeaned. As mentioned in Section I, unit root tests of the variables failed to reject the hypothesis that the federal funds rate is a random walk, so the first difference of the federal funds rate is used FYFF (denoted DFYFF) in the VAR. Without loss of generality, we can express the VAR as follows:

$$z_{t+1} = Az_t + w_{t+1} \quad (7)$$

where A is the companion matrix of the VAR and w_{t+1} is the error vector.

B. Long-Horizon Forecastability of Asset Returns

I turn now to the VAR results presented in Table II (Sample period: March 1962 to November 1994). Sequential likelihood ratio tests indicate that two lags at the monthly level are a sufficient parameterization.⁸ Using monetary policy indicators, the results suggest some short-run asset return predictability, and the R^2 of the regressions are relatively high for this type of exercise.

Tighter monetary conditions today (indicated by a high growth in the federal funds rate, or a low orthogonalized, nonborrowed, reserve growth) predict low excess returns one month ahead. However, these are still only short-horizon (one month ahead) results. For long-horizon predictability of asset returns I use the test statistic employed by Hodrick (1992). This is directly analogous to the beta coefficient of the Fama and French (1989) long-horizon regressions. I write the unconditional variance of the z_t process as

$$C(0) = \sum_{j=0}^{\infty} A^j \Omega A^j \quad (8)$$

where Ω is the variance-covariance matrix of the VAR residuals. (In empirical results the sum into infinity is truncated at j equals 500.) Furthermore, higher-order autocovariances can be estimated from $C(0)$ using $C(j) = A^j C(0)$. Then I can write the estimator of the slope coefficient of a long-horizon regression of excess returns from period $t + 1$ to period $t + k$ on a forecasting variable, denoted by $b_j(k)$, as follows:

$$b_j(k) = \frac{e1' [C(1) + \cdots + C(k)] e_j}{e_j' C(0) e_j} \quad (9)$$

where $e1$ and e_j are indicator vectors which take a value of one at the cell that corresponds to the position in z_t of the excess stock return variable and the forecasting variable we are interested in, respectively. Thus, we can estimate

⁸ The likelihood ratio test statistic is 174.48 and 47.557 when comparing one to two lags, and two to three, respectively, with corresponding marginal significance of 0.001 and 0.091 under a chi-squared distribution with 36 degrees of freedom. In any case, the results are robust to alternative specifications such as using one lag at the monthly level, or one lag at the quarterly level.

Table II
VAR Results

This table reports the excess stock return equation from a monthly two-lag vector autoregression model (VAR) containing the change in the federal funds rate (DFYFF), the portion of nonborrowed reserve growth orthogonal to total reserve growth (STRONGIN), the real interest rate (REALR), the term spread (TERM), the dividend yield (YIELD), and excess stock returns (EVW). EVW is annualized New York Stock Exchange (NYSE) value-weighted excess stock returns (source: Center for Research in Security Prices (CRSP)), constructed by subtracting the one-month T-bill rate (source: CRSP) from the monthly stock return. DFYFF is the first log difference of the CITIBASE variable FYFF. STRONGIN is the residuals from a regression of FMRNBA on FMRRRA (both Citibase variables are normalized by a 36-month moving average of FMRRRA). YIELD is constructed from the CRSP stock return series, by cumulating the future value of 12 past monthly dividends. TERM is constructed by subtracting the one-month T-bill yield (as reported by CRSP) from the Citibase series FYGT10. REALR is constructed by subtracting the first log difference of the PUNEW variable from Citibase from the one-month T-bill rate. All variables are demeaned. "Coefficient" reports the coefficient of the variable in each column, "S.E." the standard error. "F-test" reports the significance of accepting the hypothesis that the coefficients of both lags of each variable are equal to zero. The sample period runs from March 1962 to November 1994.

	Coefficient	S.E.	F-test
DFYFF _(t-1)	-2.491	5.120	
DFYFF _(t-2)	-5.276	4.533	0.322
STRONGIN _(t-1)	1.900	2.450	
STRONGIN _(t-2)	0.952	2.388	0.063
REALR _(t-1)	-0.345	0.975	
REALR _(t-2)	0.091	0.964	0.935
TERM _(t-1)	6.701	3.967	
TERM _(t-2)	-4.977	3.971	0.233
YIELD _(t-1)	49.555	42.959	
YIELD _(t-2)	-41.902	43.176	0.026
EVW _(t-1)	0.161	0.156	
EVW _(t-2)	-0.076	0.052	0.198
R ²	0.076		
Adj-R ²	0.049		
No. observations	393		

$b_j(k)$ s for each forecasting variable j we are interested in, and for different time horizons, k .

I approximate the distributions of these test statistics in three ways: First, by bootstrapping the model 1,000 times I can derive 95 percent confidence intervals for the test statistics. (This is preferable to reporting standard errors, because the distributions exhibit excess skewness and kurtosis.) Second, because the model residuals fail to pass tests of homoskedasticity, I also use GARCH(1, 1)-whitened residuals in additional bootstrapping simulations. Under the simplifying assumption that the covariance between the residuals does not change across time, I estimate each univariate GARCH model separately from each ordinary least squares (OLS) residual, using maximum likelihood. (Because the information matrix is block-diagonal, there is no loss of efficiency

by using this two-stage estimation procedure.) Finally, following the methodology of Section II, I also derive the distribution of the test statistics implied by bootstrapping the GARCH-whitened residuals under the hypothesis of no-stock-return predictability. I do this by estimating the VAR and setting the coefficients in the excess return equation equal to zero. I add bootstrapped shocks to the system and reestimate the model with time-varying expected returns 1,000 times. The resulting distribution gives the marginal significance of the test statistic under the null that the model is false and asset returns are unpredictable, but heteroskedastic.

Table III contains the estimated $b_j(k)$ s at 4, 8, 12, 18, and 24 months. A large shock to the federal funds rate, or a low level of STRONGIN, both of which indicate tighter monetary policy, predict low future excess stock returns initially, but increasing value thereafter (since the absolute level of the coefficients is declining). These results are statistically significant up to 24 months ahead for FYFF, and up to 12 months ahead for STRONGIN, irrespective of the way the test statistic distribution is estimated. This is additional evidence that monetary policy variables are significant predictors of stock returns and is consistent with the evidence presented in Section II.

C. Variance Decompositions: The Role of Monetary Policy

From equation (7):

$$(E_{t+1} - E_t)z_{t+1+j} = A^j w_{t+1} \quad (10)$$

Using equation (10), I can write each of the three stock return components of the equation (6) in terms of the parameters of our VAR:

Excess returns:

$$e_{e,t+1} \equiv (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j e_{t+1+j} = e1' \rho A (I - \rho A)^{-1} w_{t+1} \quad (11)$$

Real interest rates:

$$e_{r,t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r e_{t+1+j} = e2' (I - \rho A)^{-1} w_{t+1} \quad (12)$$

Dividend growth:

$$e_{d,t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} = e_{t+1} + e_{e,t+1} + e_{r,t+1} \quad (13)$$

where $e1$ and $e2$ are as above, I is the identity matrix, and the dividend growth component is estimated as a residual recognizing that $e_{t+1} \equiv e_{d,t+1} - e_{r,t+1} - e_{e,t+1}$ by construction.

Table III
Estimated $b_j(k)$ s

This table reports the estimated $b_j(k)$ s (row (1)) derived using a two-lag monthly vector autoregression model (VAR) containing the following variables: the change in the federal funds rate (DFYFF), the portion of nonborrowed reserve growth orthogonal to total reserve growth (STRONGIN), the real interest rate (REALR), the term spread (TERM), the dividend yield (YIELD), and excess stock returns (EVW). All variables are demeaned. The sample period is 1962:03 to 1994:11. Each $b_j(k)$ is a consistent estimator of the coefficient of a regression of forecasting variable j on excess stock returns from period $t + 1$ to period $t + k$:

$$b_j(k) = (e1'[C(1) + \dots + C(K)]e_j)/(e_j'C(0)e_j)$$

where $C(j) = A^j C(0)$, $C(0) = \sum_{j=0}^{500} A^j \Omega A^j$. Ω is the VAR variance-covariance matrix, A is the VAR companion matrix, and $e1$ and e_j are indicator vectors that take a value of one at the cell that corresponds to the VAR position of EVW and the forecasting variable in which we are interested, respectively. $C(0)$ is calculated with a truncation at j equals 500. k is measured in months. The numbers in parentheses (row (2)) are 95 percent confidence intervals derived from 1,000 bootstrapping simulations of the model. The numbers in italics and parentheses (row (3)) are 95 percent confidence intervals derived from whitening the residuals, using univariate GARCH(1, 1) and bootstrapping the model 1,000 times. Finally, the table contains (row (4)) the marginal significance of the estimated coefficients from 1,000 bootstrapping simulations using the GARCH(1, 1)-whitened residuals under the null of unpredictable excess stock returns (that is, the EVW equation in the VAR model is modified by imposing zero coefficients on all the right-hand-side variables).

	DFYFF	STRONGIN	REALR	TERM	YIELD	EVW
$k = 4$	(1) -6.931 (2) (-11.17, -2.69) (3) (-15.75, -2.33) (4) 0.008	2.205 (0.61, 3.60) (0.90, 4.23) 0.020	0.388 (-0.73, 1.52) (-0.95, 2.47) 0.520	4.288 (1.08, 7.63) (1.11, 10.12) 0.032	6.699 (3.51, 14.58) (2.14, 15.46) 0.100	0.002 (-0.04, 0.05) (-0.04, 0.16) 0.824
$k = 8$	(1) -4.548 (2) (-7.51, -1.98) (3) (-12.38, -1.39) (4) 0.008	1.591 (0.17, 2.71) (0.46, 3.30) 0.032	0.425 (-0.40, 1.29) (-0.57, 2.27) 0.272	3.358 (0.62, 6.07) (0.59, 8.51) 0.052	6.678 (372, 13.47) (2.45, 14.00) 0.080	0.004 (-0.02, 0.04) (-0.20, 0.14) 0.732
$k = 12$	(1) -3.580 (2) (-6.13, -1.37) (3) (-10.68, -0.87) (4) 0.016	1.184 (-0.05, 2.19) (0.18, 2.77) 0.052	0.390 (-0.28, 1.11) (-0.45, 2.00) 0.212	2.774 (0.37, 5.07) (0.26, 7.48) 0.056	6.699 (3.82, 12.58) (2.82, 12.95) 0.076	0.002 (-0.01, 0.02) (-0.17, 0.11) 0.776
$k = 18$	(1) -2.676 (2) (-4.74, -0.91) (3) (-8.85, -0.43) (4) 0.016	0.749 (-0.27, 1.59) (-0.06, 2.25) 0.092	0.326 (-0.24, 0.90) (-0.34, 1.71) 0.176	2.103 (-0.05, 4.06) (-0.24, 6.41) 0.064	6.608 (3.96, 11.34) (2.99, 11.60) 0.052	-0.001 (-0.01, 0.02) (-0.15, 0.09) 0.996
$k = 24$	(1) -2.074 (2) (-3.83, -0.65) (3) (-7.62, -0.25) (4) 0.020	0.448 (-0.41, 1.17) (-0.22, 1.87) 0.208	0.266 (-0.25, 0.80) (-0.30, 1.57) 0.172	1.593 (-0.28, 3.32) (-0.52, 5.44) 0.076	6.400 (3.86, 10.25) (2.97, 10.48) 0.032	-0.003 (-0.01, 0.01) (-0.01, 0.07) 0.740

Now I turn to the relative importance of my forecasting variables in shaping these results, and to the question of whether monetary policy influences asset returns mostly through dividend growth, real interest rates, or excess stock

returns. To do this I must orthogonalize the VAR shocks. Without orthogonalization, I would have to estimate variances *and* covariances between *each* variance and covariance with *each* variance and covariance of the VAR errors. This would result in a large table that would be difficult to interpret.

Therefore, I undertake standard Choleski decompositions of the VAR residuals. The initial ordering of the variables is as follows: DFYFF, STRONGIN, REALR, TERM, YIELD, and EVW. Excess stock returns are ordered last, because this article examines the formation of asset return expectations, and my underlying hypothesis is that forecasting variables precede and "cause" asset returns. (Also, with the exception of the crash in 1987, monetary authorities are usually relatively passive in their response to stock market fluctuations.) Monetary variables are ordered before financial variables, following the general motivation of this article that monetary policy shifts are reflected in the financial variables used in the finance literature to predict asset returns.

Thus I have a Choleski decomposition matrix P such that

$$v_t = P^{-1}w_t \quad \text{and} \quad E(v_t v_t') = I \quad (14)$$

where v_t are the orthogonalized shocks. I can rewrite the three components of asset returns in terms of the orthogonalized shocks, and I can calculate the effect of each orthogonalized shock j on each of the three components by estimating:

Effect of shock v_j on the excess returns component:

$$e_{e,j,t+1} = e1' \rho A (I - \rho A)^{-1} P v_{j,t+1} \quad (15)$$

Effect of shock v_j on the real interest rate component:

$$e_{r,j,t+1} = e2' (I - \rho A)^{-1} P v_{j,t+1} \quad (16)$$

Effect of shock v_j on the dividend growth component:

$$e_{d,j,t+1} = p_{1,j} v_{j,t+1} + e_{e,j,t+1} + e_{r,j,t+1} \quad (17)$$

where the $p_{1,j}$ is the $(1,j)$ element of the P matrix. The term $p_{1,j} v_{j,t+1}$ corresponds to that portion of excess stock returns, e_{t+1} , which is affected by a $v_{j,t+1}$ shock. Obviously, the sums of each component across all forecasting variables gives the total component, as analyzed previously. That is, with five components:

$$e_{e,t+1} = \sum_{j=1}^5 e1' \rho A (I - \rho A)^{-1} P v_{j,t+1} \quad (18)$$

Table IV
Decompositions Based on Orthogonalized Shocks

This table decomposes the variances and covariances between the three asset return components of a two-lag monthly vector autoregression (VAR) model into the portion of each component that is due to each of the orthogonalized errors. The VAR model consists of the change in the federal funds rate (DFYFF), the portion of nonborrowed reserve growth orthogonal to total reserve growth (STRONGIN), the real interest rate (REALR), the term spread (TERM), the dividend yield (YIELD), and excess stock returns (EVW). The sample period of the VAR runs from March 1962 to November 1994. The effect of a shock v_j on the excess returns component is

$$e_{e,j,t+1} = e1' \rho A (I - \rho A)^{-1} P v_{j,t+1},$$

on the real interest rate component,

$$e_{r,j,t+1} = e2' (I - \rho A)^{-1} P v_{j,t+1},$$

and on the dividend growth component,

$$e_{d,j,t+1} = p_{1,j} v_{j,t+1} + e_{e,j,t+1} + e_{r,j,t+1},$$

where A is the VAR companion matrix, P is the Choleski decomposition matrix, ρ is a constant, $e1$ and $e2$ are identity vectors with one in the cell corresponding to the positions of EVW and REALR, respectively, and p_{ij} is the $(1,j)$ th element of P . The sample variances and covariances of these three components are normalized by the variance of excess stock returns and multiplied by 100 so that the terms sum up to 100. Standard errors from 1,000 bootstrapping simulations of the model are in parentheses.

	DFYFF	STRONGIN	Total Monetary	REALR	TERM	YIELD	Total Financial	EVW	Total
Var(e_e, e_e)	3.39 (3.85)	0.00 (1.09)	3.39 (3.85)	2.50 (2.37)	0.47 (2.12)	90.84 (16.07)	93.81 (2.65)	0.02 (0.08)	97.22 (18.22)
2Cov(e_e, e_r)	0.36 (1.49)	0.00 (0.64)	0.36 (1.49)	-3.95 (1.97)	0.48 (1.10)	14.27 (6.94)	10.80 (2.08)	0.03 (0.06)	11.19 (8.31)
-2Cov(e_e, e_d)	-1.61 (4.06)	0.00 (1.87)	-1.61 (4.06)	2.51 (1.47)	0.24 (2.23)	-21.74 (18.48)	-18.99 (2.43)	0.81 (1.22)	-19.79 (20.83)
Var(e_r, e_r)	0.01 (0.19)	0.03 (0.18)	0.04 (0.19)	1.56 (0.57)	0.12 (0.30)	0.56 (0.61)	2.25 (0.59)	0.01 (0.02)	2.29 (0.97)
-2Cov(e_r, e_d)	-0.09 (0.71)	0.28 (0.69)	0.20 (0.71)	-1.99 (1.47)	0.12 (0.76)	-1.71 (1.88)	-3.57 (1.68)	0.60 (0.55)	-2.78 (2.81)
Var(e_d, e_d)	0.19 (1.15)	0.57 (1.26)	0.76 (1.15)	0.63 (0.91)	0.03 (0.94)	1.30 (2.24)	1.96 (1.58)	9.14 (1.67)	11.87 (3.73)
Total	2.25 (1.96)	0.89 (0.96)	3.14 (1.96)	1.27 (1.26)	1.47 (1.71)	83.53 (2.63)	86.26 (1.63)	10.60 (1.27)	100.00

(similarly for $e_{d,t+1}$ and $e_{r,t+1}$) and of course, using equation (18) I can decompose $\text{var}(e_{t+1})$ into:

$$\begin{aligned} \text{var}(e_{t+1}) = & \text{var}(e_{e,t+1}) + \text{var}(e_{r,t+1}) + \text{var}(e_{d,t+1}) + 2\text{cov}(e_{e,t+1}, e_{r,t+1}) \\ & - 2\text{cov}(e_{e,t+1}, e_{d,t+1}) - 2\text{cov}(e_{r,t+1}, e_{d,t+1}) \end{aligned} \quad (19)$$

Table IV thus displays the portions of variances and covariances of the three

components attributable to each of the forecasting variables. These are constructed by estimating the variances and covariances among the orthogonalized portions of each component, dividing by the variance of excess stock returns, and multiplying by 100, so that the terms add to 100. (Note that covariances across orthogonalized portions i, j of the same component, with $i \neq j$, are all zero by construction, since I am talking about orthogonalized shocks). For example, the top-left cell contains

$$100 \frac{\text{var}(e_{e,1,t+1}, e_{e,1,t+1})}{\text{var}(e_{t+1})} \quad (20)$$

Standard errors from bootstrapping the model 1,000 times are in parentheses.

Monetary policy variables influence the variance of the dividend growth component most, followed by the excess return component and the covariance between them. Monetary policy has little to do with future expectations of the real interest rate; REALR, the one-month real interest rate, seems to be the dominant variable here.

Monetary policy variables account for only 3.14 percent of unexpected asset return variance, versus 86.26 percent for the financial variables. This result is driven solely by the dividend yield: Shocks to this variable are responsible for most of the variance in unexpected asset returns. This is not a feature of the particular Choleski ordering: I reestimate the model, ordering the dividend yield at different positions and the results are very similar.

Two reasons explain why the dividend yield is such an integral component of unexpected asset returns. First, it is extremely persistent: A small shock to the dividend yield persists for a much longer time than a shock to other variables. Second, unexpected asset returns are dominated by changes in future excess return expectations (see the last column of Table IV), which the dividend yield predicts well. This poses an obstacle to theories that try to link asset return predictability to the business cycle, in the sense that the dividend yield is much more persistent than the latter.⁹ (I refer to the “business cycle” in a strict NBER sense). Furthermore, the fact that the inclusion of so many macroeconomic variables has not managed to absorb the predictive power of the dividend yield, shows that asset return predictability is even more difficult to model than previously thought, because most of it is driven by a variable relatively unrelated to the business cycle.

IV. Theoretical Motivation

Sections II and III establish the empirical stylized fact that monetary policy indicators are significant predictors of excess stock returns. Why should this be

⁹ Note, however, that shareholder disbursements via share repurchases and takeover premiums have surpassed cash dividends in value over the past 15 years. This fact casts doubt on conventional measures of cash-flow yields that only use cash dividends (I thank the referee for pointing this out.). It could therefore be the case that a comprehensive measure of the “cash-flow yield” would be more closely related to the business cycle.

the case? Note that we have been working with excess stock returns. That is we need an increase in expected stock returns above and beyond the increase in the riskless interest rate.

One possible explanation for the predictive power of monetary indicators relates to the so-called “financial propagation” mechanism (developed in Fazzari, Hubbard, and Petersen (1988), Bernanke and Gertler (1989), and others) as well as the “credit channel” of monetary policy transmission. (Bernanke and Gertler (1995), provide a useful summary.) Both theories describe a nonlinear world in which macroeconomic shocks are propagated depending on the financial health of the firms in the economy. The “financial propagation” mechanism amplifies and propagates shocks to firms’ balance sheets through endogenous changes in the agency costs of lending, and the spread between external and internal finance. The “credit channel” works through both the balance-sheet channel mentioned above, and through a bank lending channel, whereby a monetary policy shock leads to reduced and costlier bank-loan supply.

In such worlds, firms’ responses to macroeconomic shocks are state-dependent (or equivalently, time varying). A monetary policy shock during a tight money period has larger effects than one during easy money periods, since firms’ financial health has already declined through both worsening balance sheet income (and thus a higher need for (costlier) external finance), and through reduced bank loan supply. Given the usual risk-return tradeoff underlying most theoretical models of asset pricing, it is clear that firms’ increased vulnerability to future (unknown) macroeconomic shocks will lead to a higher expected risk premium by investors. Therefore, following the initial negative response of stock prices to monetary policy shocks, future expected returns would have to increase to compensate for the deterioration in the financial health of the firms caused by this monetary policy shock.

Is the world described above, where monetary policy affects some measure of economy-wide “riskiness,” consistent with empirical findings to date? In fact, there is significant evidence linking monetary policy to volatility and stock volatility to the business cycle. For the former, note Lastrapes’ (1989) conclusions, using an autoregressive conditional heteroskedasticity (ARCH) model, that U.S. monetary policy affects both the variance and the mean of nominal exchange rates. Whitelaw (1994) concludes that the commercial paper and Treasury bill yield spread and the one-year T-bill yield are the best predictors of conditional stock volatility. For the latter, the reader should refer to Schwert (1989a) among others, who demonstrates that stock volatility rises after stock prices fall, rises during recessions, and rises during major financial crises. Similarly, Schwert (1989b) concludes that stock market volatility, industrial production volatility, and to a lesser extent, financial volatility, all rise during recessions. Campbell, Kim, and Lettau (1993) find that aggregate market, cross-industry, and idiosyncratic firm volatility all move countercyclically during the business cycle. Finally, also note Hamilton’s (1989) results. He finds that the residuals from a regime-switching model of GNP are on average twice as large during a recession than during an expansion.

All of these stylized facts paint a world of heteroskedastic business cycles¹⁰ in which monetary policy shocks (or more generally, the stage of the business cycle) influence asset price volatility. In this context, the interpretation of the predictive power of monetary policy variables is that monetary policy shocks affect the risk structure of the economy, and also the risk characteristics of stocks.

VI. Conclusions and Implications

This article relates the results of the asset return predictability literature to macroeconomics by examining the role of monetary policy. It uncovers a new set of variables that are significant predictors of asset returns. The evidence that monetary policy variables are related to future expected excess stock returns is supported by using both Fama and French long-horizon regressions and Campbell short-horizon VARs. Contractionary monetary shocks mostly predict lower expected returns initially, and higher thereafter. Variance decompositions indicate that monetary policy shocks primarily affect expected excess returns, followed by expected dividend growth, but have little effect on expected real returns.

What implications does this evidence have for equilibrium models of asset pricing? As always, the answer depends on whether the researcher can (theoretically and empirically) account for the implied time-varying expected returns needed to support the candidate model. Even if the theoretical explanation of the predictive power of monetary indicators outlined in the previous section are to be supported empirically (a big assumption), we would still be left with the fact that the other (financial) variables remain significant in regressions that include the monetary variables. This indicates that it is not possible to fully attribute observed asset return predictability to the stance of monetary policy. Thus, we would have to account for both sources of time-varying expected returns.

This is further complicated by the fact that I find the dividend yield to be the dominant factors in the variance decompositions, the reason being that the effects of the other variables on future expected asset returns persist much less than those of the dividend yield. This poses an obstacle to theories that try to link asset pricing to the business cycle, because expected asset returns are more persistent than any macroeconomic business cycle variable.

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¹⁰ The idea that there could be autoregressive conditional heteroskedasticity in the macroeconomy as a whole seems a natural extension of ARCH models of asset prices and the idea that stocks are claims to underlying economic output.

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