What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns

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ABSTRACT

This paper uses a vector autoregressive model to decompose excess stock and 10-year bond returns into changes in expectations of future stock dividends, inflation, short-term real interest rates, and excess stock and bond returns. In monthly postwar U.S. data, stock and bond returns are driven largely by news about future excess stock returns and inflation, respectively. Real interest rates have little impact on returns, although they do affect the short-term nominal interest rate and the slope of the term structure. These findings help to explain the low correlation between excess stock and bond returns.

MAINSTREAM RESEARCH IN EMPIRICAL asset pricing has traditionally treated the variances and covariances of asset returns as being exogenous. The questions asked concern the optimal response of utility-maximizing agents to these variances and covariances, and the resulting equilibrium pattern of mean returns on securities.

Recently, however, a number of authors have challenged the finance profession to bring the second moments of asset returns within the set of phenomena to be explained. One of the first researchers to pose this challenge was Robert Shiller, who argued in the early 1980s that it is hard to account for the variance of stock returns using a model with constant discount rates.[1] Richard Roll has issued a similar challenge in a recent Presidential Address to the American Finance Association (1988), saying that "The immaturity of our science is illustrated by the conspicuous lack of predictive content about some of its most intensely interesting phenomena, particularly *changes* in asset prices."

One straightforward way to meet this challenge is to regress asset price changes on contemporaneous news events. Roll (1988) does this for individual stocks and finds that less than 40% of the variance of price changes is

[1] This research is reprinted and summarized in Shiller (1990).

typically explained by the regressions. Eugene Fama (1990a) has applied a similar methodology to the aggregate stock market. He finds that almost two-thirds of the variance of aggregate stock price movements can be accounted for by variables proxying for corporate cash flows and investors' discount rates. Fama uses leads of some variables as well as contemporaneous values, as an informal way to allow for extra information that market participants may have about future macroeconomic developments. Other recent papers using this approach include Collins, Kothari, Shanken, and Sloan (1992), Cutler, Poterba, and Summers (1989), Kothari and Shanken (1992), and Stambaugh (1990).

The use of contemporaneous regressions to explain asset price variability is appealing because it is simple, and because it is an extension of the well-established event study methodology in finance. However, this approach has little to say about the channels through which macroeconomic news variables affect asset prices. Suppose that innovations to a particular variable, say industrial production, are associated with stock market movements. This could reflect an association of industrial production with changing expectations of future cash flows, or an association with changing discount rates (perhaps because both industrial production and stock prices are responding to interest rate movements). The contemporaneous regression approach cannot distinguish these possibilities, or tell us about their relative importance.[2]

In this paper we use an alternative approach developed in Campbell and Shiller (1988a, 1988b) and Campbell (1991). Those papers study the stock market in isolation, whereas here we try to account for the variance of stock returns jointly with the variance of long-term nominal bond returns and the covariance between stock and bond returns. We first express the innovation to a long-term asset return as the sum of revisions in expectations of future real cash payments to investors, and revisions in expectations of future real returns on the asset. (Expected future returns are further broken down into expected future real interest rates and expected future excess returns on the long-term asset.) In general this asset-pricing framework holds as a log-linear approximation (Campbell and Shiller (1988a)). However, we provide an exact log-linear relation for the case in which the long-term asset is a zero-coupon bond.

We combine the asset-pricing framework with a vector autoregression (VAR) in long-term asset returns, interest rates, inflation, and other information that helps to forecast these variables. We assume that the VAR adequately captures the information used by investors. From the VAR we can calculate revisions in multiperiod forecasts of real returns and cash flows, and thus we can break asset returns into several components. In the case of stocks, the components are changing expectations of future real dividends, future real interest rates, and future excess returns on stocks. In the case of long-term nominal bonds, the components are changing expectations of future

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[2] This statement does not apply to the cross-sectional analysis of Kothari and Shanken (1992), which includes a correction for discount rate movements.

inflation rates (which determine the real value of the fixed nominal payment made at maturity), future real interest rates, and future excess returns on long bonds. The variances and covariances of these components constitute the variances of stock and bond returns, and the covariance between them.

This approach builds on the vast literature on forecasting long-term asset returns, interest rates, and inflation rates. Many recent papers have shown that dividend yields and short- and long-term interest rates have a modest degree of forecasting power for excess stock returns (Campbell (1987, 1991), Campbell and Shiller (1988a), Cutler, Poterba, and Summers (1990), Fama and Schwert (1977), Hodrick (1992), Keim and Stambaugh (1986)). The forecastability of stock returns seems to increase with the time interval over which returns are measured (Campbell and Shiller (1988b), Fama and French (1988)), although there is some dispute about the statistical properties of long-horizon forecasts in a finite sample (Nelson and Kim (1990), Richardson (1989), Richardson and Stock (1989)). Other work has shown that the slope of the term structure of interest rates helps to forecast excess bond returns (Campbell and Shiller (1991), Fama (1984), Fama and Bliss (1987), Shiller, Campbell, and Schoenholtz (1983)). There is some evidence that forecasts of excess bond and stock returns are correlated (Fama and French (1989)). At the same time, the term structure has considerable long-horizon forecasting power for nominal interest rate movements (Campbell and Shiller (1987, 1991), Fama and Bliss (1987)), and for inflation rates (Fama (1990b), Mishkin (1990)). In contrast with most of this research, our objective is not merely to forecast asset returns, but to derive the implications of our forecasts for the ex post variability of returns.

The paper closest to ours is Shiller and Beltratti (1992). The main difference is that Shiller and Beltratti concentrate more on testing hypotheses that certain components are absent from returns. In addition we distinguish more separate components of returns than do Shiller and Beltratti, we use monthly rather than annual data, we concentrate on the postwar period, and we study zero-coupon bonds of various maturities while Shiller and Beltratti look at consols and other long-maturity coupon bonds.

The organization of the paper is as follows. Section I describes the asset-pricing framework for stocks and bonds, and explains our VAR methodology. Section II presents empirical results for U.S. data over the period 1952 to 1987, while Section III concludes.

I. Asset Prices, Expected Returns, and Unexpected Returns

In this section we first use the log-linear approximate asset pricing framework of Campbell and Shiller (1988a) and Campbell (1991) to express unexpected excess stock returns as a function of news about future dividend growth rates, real interest rates, and excess stock returns. We develop the corresponding expression for nominal zero-coupon bonds, which holds exactly rather than as an approximation. Using the same framework, we then show why asset prices, yields, and yield spreads are useful for forecasting long-

.horizon returns, and we obtain news components for innovations in yields and yield spreads. Finally, we explain how to use VAR systems to obtain empirical proxies for the news components of innovations.

A. *Expected and Unexpected Stock Returns*

The basic equation for stock returns relates the unexpected excess stock return in period $t + 1$ to changes in rational expectations of future dividend growth, future real interest rates, and future excess stock returns. We write e_{t+1} for the log excess return on a stock held from the end of period t to the end of period $t + 1$, relative to the return on short debt. We write d_{t+1} for the log real dividend paid during period $t + 1$, and r_{t+1} for the log real interest rate from t to $t + 1$. Then the equation is

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

Here E_t denotes an expectation formed at the end of period t, conditional on an information set that includes at least the history of stock prices and dividends, while Δ denotes a one-period backward difference. The parameter ρ comes out of the log-linear approximation procedure; it is a number a little smaller than one (0.9962 in our empirical work).

Equation (1) is not a behavioral model; rather, it is a dynamic accounting identity that imposes internal consistency on expectations. If the unexpected excess stock return is negative, then either expected future dividend growth must be lower, or expected future real stock returns must be higher, or both. To see why, consider an asset with fixed dividends whose price falls. Its dividend yield is now higher; this will increase the asset return unless there is a further capital loss. Capital losses cannot continue forever, so at some point in the future the asset must have higher real returns. These may come either in the form of higher real interest rates, or in the form of higher excess returns on stock relative to short-term debt.

The discounting at rate ρ in equation (1) means that an increase in stock returns expected in the distant future is associated with a smaller drop in today's stock price than is an increase in stock returns expected in the near future. To understand why this is, consider the arrival of news that stock returns will be higher ten periods from now. If the path of dividends is fixed, the stock price must drop to allow a rise ten periods from now. Most of the drop occurs today, but for nine periods there are smaller declines which are compensated by a higher dividend yield. These further declines reduce the size of the drop which is required today.

Formally, equation (1) is derived by taking a first-order Taylor approximation of the equation relating the log stock return to log stock prices and dividends. The approximate equation is solved forward, imposing a terminal condition that the log dividend-price ratio does not follow an explosive

process. Details are given in Campbell and Shiller (1988a) and Campbell (1991).

It will be convenient to simplify the notation in equation (1). Let us define $\tilde{e}_{t+1}$ to be the unexpected component of the excess stock return e_{t+1}, $\tilde{e}_{d,t+1}$ to be the term in equation (1) that represents news about cash flows, $\tilde{e}_{r,t+1}$ to be the term that represents news about real interest rates, and $\tilde{e}_{e,t+1}$ to be the term that represents news about future excess returns. Thus we use a tilde to denote an innovation or surprise in a variable, and we use subscripts to denote the news components making up that surprise. Then equation (1) can be rewritten as

$$\tilde{e}_{t+1} = \tilde{e}_{d,t+1} - \tilde{e}_{r,t+1} - \tilde{e}_{e,t+1}. \tag{2}$$

B. Expected and Unexpected Bond Returns

The basic equation for bond returns has a form similar to the basic equation for stock returns. We define $x_{n,t+1}$ to be the log excess one-period return on an n-period zero-coupon bond held from time t to time $t + 1$. (At time $t + 1$, the bond becomes an $(n - 1)$-period bond.) As before, we use a tilde to denote an innovation. We define π_{t+1} to be the log one-period inflation rate from t to $t + 1$. Then we have

$$\tilde{x}_{n,t+1} = (E_{t+1} - E_t) \left\{ -\sum_{i=1}^{n-1} \pi_{t+1+i} - \sum_{i=1}^{n-1} r_{t+1+i} - \sum_{i=1}^{n-1} x_{n-i,t+1+i} \right\}$$
$$= -\tilde{x}_{\pi,t+1} - \tilde{x}_{r,t+1} - \tilde{x}_{x,t+1}. \tag{3}$$

This equation is derived in Appendix A. Like the stock decomposition (1) it is a dynamic accounting identity rather than a behavioral model, but unlike (1) it holds exactly rather than as an approximation. It says that unexpected excess bond returns must be associated either with decreases in expected inflation rates over the life of the bond, or with decreases in expected future real returns on the bond. The latter can take the form either of decreases in future real interest rates, or of decreases in future excess bond returns. Note that the maturity of the bond shrinks as time passes, so the relevant expectations are for the returns on a bond that will have a maturity of $(n - i)$ at time $t + i$.[3] Changes in expected inflation rates appear in (3) because they alter the expected real value of the fixed nominal payoff on the bond, so they can cause capital gains and losses even if expected real bond returns are constant.

In the literature on the term structure of interest rates, the "expectations theory of the term structure" states that the third term on the right-hand side of (3) is always zero; the "Fisher hypothesis" states that the second term is always zero. When both these hypotheses hold, then only the first term

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[3] Also note that the summation in the first two terms on the right-hand side of (3) could start at 0 rather than 1, and the equation would remain valid. The two extra terms would cancel out because they add to the nominal interest rate, which is known at time t.

varies through time and changing expected inflation is the only source of unexpected, capital gains and losses on long bonds relative to short bonds.

C. Prices, Yields, and Yield Spreads

Several authors have recently found that long-term asset prices can be surprisingly powerful forecasting variables. To eliminate apparent unit roots in the raw series, prices are most commonly used as elements of yields or yield spreads. For example, Campbell and Shiller (1988a, 1988b) and Fama and French (1988) use dividend yields to forecast stock returns, while Campbell and Shiller (1991), Fama (1990b), and Mishkin (1990) use bond yield spreads to forecast future bond returns, interest rates, and inflation rates. The forecasting power of asset price variables is particularly evident when forecasts are made over long horizons.

The log-linear framework described above can be used to interpret these findings. In the stock market, for example, the log dividend-price ratio or dividend yield satisfies

$$d_t - p_t = E_t \sum_{j=0}^{\infty} \rho^j [-\Delta d_{t+1+j} + r_{t+1+j} + e_{t+1+j}]. \tag{4}$$

This equation helps to explain why the dividend-price ratio has forecasting power for excess stock returns at long horizons. The third term on the right hand side of (4) is approximately equal to the conditional expectation of the long-horizon excess return. Provided that the other two terms on the right-hand side of (4) are not too variable, the dividend-price ratio should perform well as a proxy for the long-horizon expected excess return. More generally, if there is *any* variation in the expected excess return, the dividend-price ratio should have some forecasting power.

A similar point can be made for bonds, without the use of any log-linear approximation. In the case of bonds, it is conventional to begin by transforming nominal prices to yields to maturity. The nominal log yield to maturity, $y_{n,t}$, is minus the nominal log bond price divided by n. To eliminate an apparent unit root in nominal interest rates, one can work with the difference or yield spread between the n-period nominal interest rate and the 1-period nominal interest rate, $s_{n,t} \equiv y_{n,t} - y_{1,t}$. This variable can be written as

$$s_{n,t} = \left(\frac{1}{n} \right) E_t \sum_{i=0}^{n-1} [(n - 1 - i)(\Delta \pi_{t+2+i} + \Delta r_{t+2+i}) + x_{n-i,t+1+i}]. \tag{5}$$

Equation (5) relates the nominal yield spread to expected future changes in inflation rates and real interest rates, and to expected excess returns on long bonds. The expectations theory of the term structure makes the third term on the right-hand side of (5) constant, while the Fisher hypothesis makes the second term on the right-hand side zero. These hypotheses are extreme. In general, the nominal yield spread will be a useful proxy for expectations of all the terms on the right-hand side. This helps to explain why yield spreads

help to forecast long-horizon movements in inflation and interest rates, as well as excess returns on long bonds.[4]

Innovations in bond returns are closely related to innovations in bond yields, short rates, and yield spreads. Again using tildes for innovations, we have

$$\tilde{x}_{n,t+1} = -(n-1)\tilde{y}_{n-1,t+1} = -(n-1)(\tilde{y}_{1,t+1} + \tilde{s}_{n-1,t+1}), \qquad (6)$$

so a decomposition of the bond return can be reinterpreted as a decomposition of the bond yield or the sum of the short-term interest rate and the n-period yield spread. From (6) it follows that innovations in the short rate and yield spread, respectively, can be decomposed as

$$\tilde{y}_{1,t+1} = -\tilde{x}_{2,t+1} = (E_{t+1} - E_t)[\pi_{t+2} + r_{t+2}]$$
$$= \tilde{y}_{\pi,t+1} + \tilde{y}_{r,t+1}, \qquad (7)$$

and

$$\tilde{s}_{n-1,t+1} = \tilde{x}_{2,t+1} - \frac{\tilde{x}_{n,t+1}}{(n-1)}$$
$$= \frac{(E_{t+1} - E_t)}{(n-1)} \sum_{i=1}^{n-1} [(n-1-i)(\Delta\pi_{t+2+i} + \Delta r_{t+2+i}) + x_{n-i,t+1+i}]$$
$$= \tilde{s}_{\pi,t+1} + \tilde{s}_{r,t+1} + \tilde{s}_{x,t+1}. \qquad (8)$$

These equations say that short rate innovations are driven by changing expectations of inflation and real interest rates one period ahead. Yield spread innovations are determined by changing expectations of longer-term *changes* in inflation and real interest rates between the next period ahead and the more distant future, and also by changing expectations of future excess returns on long-term bonds.

D. Variance Decomposition with Correlated Components

So far we have stated a number of identities relating innovations in long-term asset returns to revisions in investors' expectations of future dividends, real interest rates, inflation rates, and excess long-term asset returns. Our objective is to use these identities to estimate the relative importance of the different components for the historical behavior of asset returns.

One immediate difficulty is that the various components may be correlated with one another. For concreteness, consider the decomposition of excess stock returns. Equation (2) implies that the variance of excess stock returns

[4] Chen (1991), Estrella and Hardouvelis (1991), and Stock and Watson (1990) show that yield spreads also help to forecast the level of economic activity. Equation (5) should be helpful in thinking about why this is so.

can be written as

$$\mathrm{Var}(\tilde{e}_{t+1}) = \mathrm{Var}(\tilde{e}_{d,t+1}) + \mathrm{Var}(\tilde{e}_{r,t+1}) + \mathrm{Var}(\tilde{e}_{e,t+1})$$
$$- 2\,\mathrm{Cov}(\tilde{e}_{d,t+1}, \tilde{e}_{r,t+1}) - 2\,\mathrm{Cov}(\tilde{e}_{d,t+1}, \tilde{e}_{e,t+1})$$
$$+ 2\,\mathrm{Cov}(\tilde{e}_{r,t+1}, \tilde{e}_{e,t+1}). \tag{9}$$

One way to state a variance decomposition is simply to report the six numbers on the right-hand side of (9), and we do this in our empirical work below. A number like $\mathrm{Var}(\tilde{e}_{d,t+1})$ answers the question, "What would the variance of stock returns be if the process for stock dividends remained unchanged, but interest rates and expected excess stock returns became constant?". Whether this question is meaningful depends on the context. In an exchange economy, for example, stock dividends are modeled as an exogenous endowment while interest rates and expected excess stock returns depend on the dividend process and on the risk aversion of a representative agent. In such an economy one could imagine reducing the risk aversion of the representative agent to zero, while leaving the endowment process unchanged. The effect of this would be to change the variance of stock returns to $\mathrm{Var}(\tilde{e}_{d,t+1})$.

Alternatively, one may want to transform the components in (9) so that they are orthogonal to one another. $\mathrm{Var}(\tilde{e}_{t+1})$ can then be written as a sum of variances of the orthogonalized components. One simple and popular way to orthogonalize components is to order them and then apply a Cholesky decomposition. The variance of the first component in such an ordering is given by the variance of the fitted value in a simple regression of $\tilde{e}_{t+1}$ on that component.

It is tempting to think that a component will have the largest share of variance when it is given first place in the ordering, in other words that the R^2 statistic of a simple regression of $\tilde{e}_{t+1}$ on a component will be an upper bound on the variance share of that component. Unfortunately this is incorrect. It is possible for a component to have a larger share of variance when it is placed lower in the ordering. To see this, note that if one component is negatively correlated with the others then it can be uncorrelated with the sum of the components. This component will get a zero share of variance when it is ordered first, but in general it will get a nonzero share when it is given a lower place in the ordering. Below we show that this is not just a theoretical possibility, but occurs in some of our asset return decompositions. For similar reasons the sum of the R^2 statistics from simple regressions on all the individual components may be either greater or less than one, which would be the R^2 from a multiple regression on the components. Despite this difficulty of interpretation, the simple R^2 statistic is a popular measure of the importance of a component, and we report this measure in our empirical work.

Although correlation among components leads to ambiguity in the notion of a variance decomposition, this does not mean that the decomposition summarized by (9) is uninteresting when the components are correlated. The obser-

vation that the various components of an asset return are highly correlated may itself be an important stylized fact.

E. Empirical Proxies for Unobservable Components

In practice the expectational revisions in equations (2) and (3) are not directly observable. Cutler, Poterba, and Summers (1989), Fama (1990a), and Stambaugh (1990) have used contemporaneous regressions to deal with this problem. As we noted above, a popular if problematic measure of the importance of a particular component is the variance of the fitted value obtained when $\tilde{e}_{t+1}$ is regressed on that component. The contemporaneous regression approach uses instead a vector of explanatory variables w_{t+1} that proxies for the unobserved component. The variance of the fitted value obtained in a regression of $\tilde{e}_{t+1}$ on w_{t+1} is taken as an estimate of the variance of the fitted value that would be obtained if $\tilde{e}_{t+1}$ were regressed on the component itself.

Even when a good proxy vector is available in the sense that the unobserved component can be written as a linear combination of the variables in w_{t+1}, the contemporaneous regression approach can run into difficulties. The problem is that the variance of the unobserved component will be overstated if other components of $\tilde{e}_{t+1}$ are correlated with elements of w_{t+1}. Such correlation is possible even when the components of $\tilde{e}_{t+1}$ are uncorrelated with each other.

Because of these difficulties with contemporaneous regressions, we use a vector autoregressive (VAR) approach instead. This approach is more ambitious in that it seeks to use the time-series structure of the problem to identify revisions in expectations. The VAR approach postulates that the unobserved components of returns can be written as linear combinations of innovations to observable variables. The coefficients in these linear combinations are identified by using a time-series model to construct forecasts of the discounted value of future dividends, real interest rates, excess returns, and so forth. Revisions in these forecasts are then used as proxies for revisions in investors' expectations. This approach must confront two problems. First, the relevant expectations are of variables that are realized only over very long periods of time. (In the case of stocks, in fact, the expectations concern the infinite future.) Second, investors may have information that is not available to us.

We handle the first problem by using a VAR model to calculate multiperiod expectations. In effect, we use the short-run behavior of the variables to impute the long-run behavior. This procedure seems to have better finite-sample properties than direct regression methods with long-horizon variables, although of course it is necessary to assume that the VAR adequately captures the dynamics of the data.[5]

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[5] VARs are used by Campbell and Shiller (1987, 1988a, 1988b) and Kandel and Stambaugh (1988). Fama and French (1988a, 1988b) pioneered the use of long-horizon regressions. The finite-sample properties of such regressions are investigated by Richardson and Stock (1989) and Hodrick (1992); Hodrick explicitly compares them with VAR procedures. Campbell (1991) also undertakes a Monte Carlo study of the properties of VAR variance decompositions.

The second problem is more difficult. In general there is no way to rule out the possibility that investors may have information, omitted from our VAR, that affects the decomposition of variance. A special case where investors' superior information causes no problem occurs when only one component of an asset price is time varying. In this case the asset price itself summarizes all the information investors have about that component (Campbell and Shiller (1987)). Thus if one is interested in testing the hypothesis that expected real interest rates and excess returns on long bonds are constant, this can be done using a VAR that includes the long bond yield or yield spread; under the null hypothesis the yield varies only because expected inflation varies, so it embodies all the relevant information about inflation that investors possess. When several components of an asset price are variable, however, the asset price will be an imperfect proxy for investors' information about any one component. In this case the VAR results must be interpreted more cautiously, as giving a variance decomposition conditional on whatever information is included in the system. In practice it seems likely that the VAR results will tend to overstate the importance of whichever component is treated as a residual, but the sign of the bias will depend on the covariances between omitted and included variables.

The VAR approach begins by defining a vector of state variables that help to measure or forecast excess returns. These variables are chosen to be stationary, and for notational convenience we treat them as having zero means. (In our empirical work we remove sample means from all variables before estimating the VAR process.)

In order to measure excess returns and their components, our state vector must include at least the excess stock return, the real interest rate, the change in the nominal interest rate, and the long-short yield spread. In addition we use two other variables that have been shown to forecast excess bond and stock returns, real interest rates, and inflation rates. These variables are the dividend-price ratio and the "relative bill rate." The dividend-price ratio is included as a good forecaster of stock returns, and also because the return decomposition holds only conditional on an information set that includes the stock price itself. The relative bill rate, which is given further motivation below, is defined as the level of the short rate relative to a 1-year backwards moving average of short rates, or equivalently as a triangular 1-year moving average of changes in short rates. We use the notation rb_t for the relative bill rate, where

$$rb_t \equiv y_{1t} - \left(\frac{1}{12}\right)\sum_{i=1}^{12} y_{1,t-i} = \sum_{i=0}^{12}\left(1 - \frac{i}{12}\right)\Delta y_{1,t-i}. \qquad (10)$$

Writing z_t for the state vector and making the relative bill rate the last element, we have

$$z_t = [e_t, r_t, \Delta y_{1,t}, s_{n,t}, d_t - p_t, rb_t]'. \qquad (11)$$

Next we assume that the state vector follows a first-order VAR process:

$$z_{t+1} = Az_t + w_{t+1}. \tag{12}$$

The matrix A is the coefficient matrix of the VAR, and w_t is the error vector. The assumption that the VAR is first-order is not restrictive; higher-order VAR models are handled by augmenting the state vector and reinterpreting A as the companion matrix of the system. We also define vectors $e1$ through $e4$ as the first four columns of a 6×6 identity matrix. The vector ei is used to pick out the ith element of the state vector.

Innovations to excess returns can now be obtained directly from the VAR error vector. We have $\tilde{e}_{t+1} = e1'w_{t+1}$ simply from the fact that e_{t+1} is the first element of the state vector. The bond return innovation can be obtained from the innovation in the short-term interest rate, $\tilde{y}_{1,t+1} = e3'w_{t+1}$, and the innovation in the long-short yield spread, $\tilde{s}_{n,t+1} = e4'w_{t+1}$. From equation (6) we then have $\tilde{x}_{n,t+1} = -(n-1)(e3' + e4')w_{t+1}$.[6] To obtain VAR estimates of revisions in long-horizon expectations, we use the fact that

$$(E_{t+1} - E_t)z_{t+1+j} = A^j w_{t+1}. \tag{13}$$

This can be used to calculate each of the components of portfolio returns as a linear combination of the elements of the error vector w_{t+1}.

For stock returns, we obtain the components $\tilde{e}_e$ and $\tilde{e}_r$ by forecasting excess stock returns and real interest rates respectively. Our analysis is conditioned on the assumption that the VAR captures the exact dynamics of the expected return process. Thus we can estimate news about discount rates directly from the VAR, and we attribute any remaining component of the unexpected excess stock return to news about dividends. This enables us to avoid using an explicit model of the dividend process. We give details of this procedure in Appendix B.

One could instead include dividend growth rates in the vector z_t, leaving some other term to be the residual. However this would have two important disadvantages. First, monthly dividends display seasonal variation, which would need to be handled as part of the forecasting procedure. Second, there is some doubt as to whether dividends follow a linear time-series model with constant coefficients. The Modigliani-Miller propositions on the irrelevance of dividend policy give us no theoretical reason to expect managers to pursue any particular dividend policy. Some have argued that this undermines empirical work that applies standard time-series methods to dividends. Lehmann (1991, p. 1), for example, says that "The conventional practice of assuming a particular dividend policy and computing its present value is fraught with hazard.... There is substantial reason to believe that any assumed dividend policy is misspecified since managers have no obvious

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[6] These formulas use the fact that the innovation in the level of the short rate is the same as the innovation in the change of the short rate, since investors know the lagged short rate level beforehand. Also we ignore the distinction between $s_{n,t}$ and $s_{n-1,t}$. This introduces an approximation error that is very small when n is large.

incentive to adopt or maintain a consistent dividend policy." Whatever the merits of Lehmann's argument, it does not apply here since we do not model the timing of dividend payments as opposed to their present value.

For bond returns, we first note that the change in inflation can be obtained from the elements of the state vector as $\Delta \pi_{t+1} = \Delta y_{1,t} - \Delta r_{t+1}$, so the innovation in the change in inflation and the innovation in the ex post real interest rate both equal $-e2'w_{t+1}$. One component of the excess bond return is a sum of revisions in expected inflation levels, but this can be rewritten as a weighted sum of revisions in expected inflation changes. We obtain inflation and real interest rate components by direct forecasting, leaving the revision in expected excess returns as the residual. This choice of residual is forced on us because we cannot directly measure the sequence of excess returns on the bond as its maturity shrinks over its remaining life. The components of slope and level portfolio returns are calculated in the analogous manner to the components of bond returns. The formulas for these components are given in Appendix B.

The one remaining issue to address is how we calculate standard errors for statistics such as the variance of a particular component of returns. Our approach is to treat the VAR coefficients, and the elements of the variance-covariance matrix of VAR innovations, as parameters to be jointly estimated by Generalized Method of Moments (Hansen (1982)). The GMM parameter estimates are numerically identical to standard OLS estimates, but GMM delivers a heteroskedasticity-consistent variance-covariance matrix for the entire set of parameters (White (1984)). Call the entire set of parameters γ, and its variance-covariance matrix V. Consider a statistic such as the variance of news about future excess stock returns relative to the variance of unexpected stock returns. This can be written as a nonlinear function $f(\gamma)$ of the parameter vector γ. Then we estimate the standard error for the statistic in standard fashion as $\sqrt{f_\gamma(\gamma)'Vf_\gamma(\gamma)}$.

II. An Application to Postwar U.S. Data

A. Data and Sample Period

We now apply our methods to postwar U.S. data on stock and bond returns. Our stock index is the value-weighted index of stocks traded on the NYSE and AMEX, as calculated by the Center for Research in Security Prices (CRSP) at the University of Chicago. We measure the dividend yield on the index in a standard fashion, taking total dividends paid over the previous year relative to the current stock price.

For nominal interest rates, we use McCulloch's (1990) data set on zero-coupon yields implied by the yield curve for U.S. Treasury securities. At maturities beyond one year, U.S. Treasury securities pay coupons so McCulloch uses a cubic spline method to calculate an implied zero-coupon yield curve. The method fits end-of-month security prices (measured as the average of bid and asked quotations), taking account of the difference between the

ordinary income tax rate and the capital gains tax rate (McCulloch, 1975). This tax effect had an important influence on the prices of heavily discounted bonds during the 1950s and 1960s, but has been relatively unimportant since then. In the earlier part of the sample McCulloch includes some "flower bonds" (redeemable at par for the payment of estate taxes) in the set of bonds, but he does exclude those flower bonds whose prices appear to have been most affected by the estate tax feature.

Campbell and Shiller (1991) also use the McCulloch data. They compare the properties of this data set with the main alternative zero-coupon yield series, due to Eugene Fama and Robert Bliss and available from CRSP. Fama and Bliss's data set has the advantage that it is available up to the present, but the disadvantage that the longest maturity is five years. Campbell and Shiller find that the two data sets give very similar results at comparable maturities, and this increases our confidence in the McCulloch data.

The McCulloch data are available at the beginning of each month from 1947:1–1987:3, but we start our sample in 1952:1 in order to avoid the period before the 1951 Treasury-Fed Accord. We set n, the maturity of our long bond, equal to 10 years (120 months) as this is the longest maturity that is available throughout the sample period. We calculate the log bond return as the change in log price, where log price is minus the number of months to maturity times the McCulloch log yield.

Our final piece of data is a price index for deflating nominal asset returns. We use the Consumer Price Index, adjusted before 1983 to reflect the improved treatment of housing costs that is used in the official index only after 1983.

Throughout the paper we report results for the full sample period 1952:1–1987:2, as well as for subsamples 1952:1–1979:9, 1952:1–1972:12, and 1973:1–1987:2. The first of these subsamples is chosen to exclude the period after the change in Federal Reserve operating procedures in October 1979. The level and volatility of interest rates increased considerably during the 1979–82 period, and it may be unreasonable to impose a constant linear time-series model on the pre- and post-1979 data together. The second subsample is chosen because it has been argued (Fama (1975)) that the real interest rate was constant during the 1950s and 1960s; this would imply that all movements in nominal interest rates during this period were due to changing expectations of future inflation (and perhaps term premiums on longer-maturity bonds). The third subsample is the complement of the second subsample.

Table I reports some basic summary statistics about the second moments of innovations in the excess stock return, the excess 10-year bond return, the 1-month bill rate, and the 10-year–1-month yield spread. Excess returns are measured over the return on a 1-month Treasury bill, in percentage points per month, while the short rate and yield spread are measured in percentage points per year. Innovations were calculated from the first-order VAR system described below; naturally results are very similar if raw excess bond and stock returns are used. Given the units used in the table, the bond return

Table I

Variances, Covariances, and Correlations of Stock and Bond Returns

$\tilde{e}_t$ and $\tilde{x}_t$ are the innovations in excess returns on stocks and 10-year zero-coupon bonds, relative to 1-month bills. $\tilde{y}_{1t}$ and $\tilde{s}_t$ are the innovations in the 1-month nominal bill rate and the yield spread between 10-year zero-coupon bonds and 1-month bills. Returns are measured in percentage points per month, while the bill rate and yield spread are measured in percentage points at an annual rate. Sample variances and covariances are shown along and below the diagonal of each matrix; correlations are shown in bold face above the diagonal.

		$\tilde{e}_t$	$\tilde{x}_t$	$\tilde{y}_{1t}$	$\tilde{s}_t$
	$\tilde{e}_t$	15.500	**0.198**	**−0.084**	**−0.010**
1952:1–1987:2	$\tilde{x}_t$	2.310	8.802	**−0.446**	**−0.028**
	$\tilde{y}_{1t}$	−0.210	−0.840	0.403	**−0.882**
	$\tilde{s}_t$	−0.023	−0.047	−0.318	0.323
		$\tilde{e}_t$	$\tilde{x}_t$	$\tilde{y}_{1t}$	$\tilde{s}_t$
	$\tilde{e}_t$	14.172	**0.095**	**−0.116**	**0.075**
1952:1–1979:9	$\tilde{x}_t$	0.689	3.709	**−0.362**	**−0.125**
	$\tilde{y}_{1t}$	−0.177	−0.283	0.164	**−0.880**
	$\tilde{s}_t$	0.107	−0.091	−0.136	0.145
		$\tilde{e}_t$	$\tilde{x}_t$	$\tilde{y}_{1t}$	$\tilde{s}_t$
	$\tilde{e}_t$	12.026	**0.082**	**−0.116**	**0.068**
1952:1–1972:12	$\tilde{x}_t$	0.536	3.581	**−0.342**	**−0.273**
	$\tilde{y}_{1t}$	−0.126	−0.203	0.098	**−0.811**
	$\tilde{s}_t$	0.072	−0.158	−0.078	0.094
		$\tilde{e}_t$	$\tilde{x}_t$	$\tilde{y}_{1t}$	$\tilde{s}_t$
	$\tilde{e}_t$	19.482	**0.261**	**−0.065**	**−0.058**
1973:1–1987:2	$\tilde{x}_t$	4.655	16.362	**−0.475**	**0.034**
	$\tilde{y}_{1t}$	−0.264	−1.762	0.841	**−0.896**
	$\tilde{s}_t$	−0.205	0.112	−0.664	0.652

innovation is $-(n - 1)/12 \approx -10$ times the sum of the short rate and yield spread innovations. For each sample period we report variances and covariances (on and below the diagonal) and correlations (in bold face above the diagonal).

The main results in Table I are as follows. Looking first at the variances of excess return innovations, we see that stock returns are more volatile than 10-year bond returns but the difference in variance is much larger in the early part of the sample. In 1952–72, the stock variance is almost 4 times as large as the bond variance, whereas in 1973–87 the difference in variance is less than 20%. The reason for this is mainly a dramatic increase in the

variance of bond returns, associated with increases in the variances of both short rate innovations and yield spread innovations.

As for the correlations, the most striking feature of Table I is the low but increasing correlation between excess returns on stocks and bonds. Conventional wisdom is that long-term asset prices move (or should move) together, and indeed it is true that stock and bond returns are always positively correlated. But the correlation is tiny at 0.08 in the 1952–72 period, increasing to 0.26 in the 1973–87 period. Over the full sample, the two asset returns have a modest positive correlation of 0.20. The correlation of stock returns with short rate innovations is somewhat more stable, ranging from -0.07 to -0.12; the increase in the stock-bond correlation is due largely to a change in the correlation between stock returns and yield spread innovations. Finally, we note that the correlation between short-rate innovations and yield spread innovations is always large and negative, lying between -0.8 and -0.9 in every sample. This reflects the fact that long-term interest rates are smoother than short-term rates, so an increase in short-term rates tends to be associated with a decline in the yield spread.

The next step is to conduct the VAR analysis described in the previous section. Our VAR system includes six variables: the excess stock return, real interest rate, change in the nominal 1-month interest rate, and 10-year–1-month yield spread, which are needed to measure returns and their components; and the dividend-price ratio and relative bill rate, which are useful forecasting variables. The main variable that may need some discussion is the relative bill rate. This is defined to be the current 1-month bill rate, less a backwards 1-year moving average of bill rates. Equivalently, it can be described as a triangular 1-year moving average of past changes in bill rates. The relative bill rate helps to capture some of the longer-run dynamics of changes in interest rates without introducing long lags, and hence a large number of parameters, into the VAR system.[7]

All the variables in the VAR system appear to be stationary in our sample period. Dickey-Fuller tests and augmented Dickey-Fuller tests with 4 lags reject the unit root hypothesis at the 5% level or better for each series included in the VAR. While there may be size problems with unit root tests in finite samples, the test results suggest that stationary asymptotic distributions are likely to approximate well the finite sample distributions of VAR coefficients and test statistics.

The number of variables in the VAR increases very rapidly with the lag length, so there is some danger of overfitting when a high-order VAR is used. For this reason we report results from a parsimonious first-order VAR in the full sample and all subsamples. We also give results from a third-order VAR estimated over the full sample, to show that our findings are robust to VAR lag length. Over the full sample, a Wald test for joint significance of the second-lag variables when these are added to the first-order VAR provides

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[7] The relative bill rate is also used by Campbell (1991) and Hodrick (1992).

strong evidence that a second lag should be included. There is weaker evidence for a third lag; the third-lag variables are jointly significant at the 5% level only in the forecasting equation for the dividend-price ratio. We also calculated variance decompositions for a six-lag VAR, which were similar to those reported.

Table II reports the matrix of estimated first-order VAR coefficients for the full sample and each subsample. This is the matrix A in the notation of the previous section. The variables in the table are measured in percentage points per year with the exception of the stock return, which is measured in percentage points per month. Asymptotic heteroskedasticity-consistent standard errors are reported below the coefficient estimates. Although there are 36 coefficients in the matrix, many of these are numerically small and statistically insignificant. The one-period dynamics of the system can be succinctly described as follows.

In forecasting the excess stock return, the dividend-price ratio and long-short yield spread enter positively while the short-term interest rate variables, the change in the short rate and the relative bill rate, enter negatively. This sign pattern is stable across all subsamples, although there are some shifts in the magnitude and statistical significance of the coefficients. The ex post real interest rate process is rather simpler, being an AR(1) with a coefficient of about 0.4 in the full sample. In the 1952–72 subsample, however, the lagged real interest rate drops out of the real interest rate forecasting equation, and only the relative bill rate is statistically significant. The real interest rate equation has an R^2 statistic of only 5% in this period.[8] The change in the short rate is hard to forecast, consistent with the fact that the nominal bill rate is close to a random walk; however the yield spread and relative bill rate do have some forecasting power in the earlier subsamples. The yield spread itself follows a persistent AR(1) process with a coefficient between 0.8 and 0.9 in every subsample; in addition the change in the short rate and the relative bill rate help to forecast the yield spread in the earlier subsamples. The dividend-price ratio is forecast by its own lag, with a coefficient very close to one, and by the lagged excess stock return, with a small but highly significant negative coefficient. Finally, the relative bill rate is forecast by its own lag and by the lagged yield spread.[9]

This completes our summary of the one-period behavior of the variables. We now turn to our variance decompositions, which depend on the longer-run dynamics of the system as described by the infinite discounted sum of powers of the coefficient matrix.

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[8] This is broadly consistent with Fama's (1975) claim that the ex ante real interest rate was constant in the 1950s and 1960s. Even in the 1952–72 period, however, we find that our forecasting variables are jointly statistically significant. Fama (1976) also found some evidence for real interest rate variation in this period.

[9] The presence of some own lag coefficients very close to one in the coefficient matrix should not be taken as evidence that the system is nonstationary. Univariate tests reject the hypothesis of a unit root for each variable in the VAR, and the largest root of the multivariate system is 0.970 in the full sample.

B. A Variance Decomposition for Excess Stock Returns

In Table III we report the variance decomposition implied by the VAR for excess stock returns. The first row of the table shows the R^2 when the VAR is used to forecast the monthly excess stock return, along with the joint significance level of the forecasting variables. Then the table reports the variances and covariances of the different components of the return. These are normalized by the variance of the return innovation itself so the numbers reported are shares that add up to one. Finally the table shows the implied R^2 statistics that would be obtained in simple regressions of the unexpected excess return on each of the estimated components. As discussed above, these R^2 statistics are alternative measures of the importance of components. The variance and covariance shares and implied R^2 statistics of the components are reported with asymptotic standard errors, reflecting the fact that the components are not directly observed but are estimated from a VAR system.

The stock return results in Table III are similar to those reported in Campbell (1991). The R^2 for forecasting excess stock returns at a monthly frequency is quite modest, ranging from 6% in the 1952–72 period to 13% in the 1973–87 period. The joint significance of the forecasting variables is 1% in the 1952–72 period, and better than 0.1% in all other sample periods.

Despite the modest degree of forecasting power for stock returns, the full sample variance decomposition attributes only 15% of the variance of stock returns to the variance of news about future dividends, and 70% to the variance of news about future excess returns. The decompositions for sub-samples are fairly similar; the variance of news about future dividends is never more than 20% of the variance of excess returns, while the variance of news about future excess returns is never less than 55% of the variance. Simple regressions of unexpected excess stock returns on the estimated components tell a similar story. In the full sample, news about future excess returns can explain (in the sense of least-squares regression) more than 85% of the variance of unexpected excess stock returns, while news about future dividends explains only 20% of the variance. Across subsamples, news about excess returns never explains less than 85% and news about dividends never explains more than 60% of the variance. (This 60% figure is achieved in the 1952–72 period; in other periods news about dividends explains no more than 25% of the variance of excess stock returns.)

These results may seem surprising at first. The VAR system forecasts only a small share of the monthly variance of excess stock returns; yet at the same time it attributes most stock market variation to changing expected excess returns. Campbell (1991) explains how these properties of the system are consistent with one another, and we do not repeat his discussion in detail here. The key point is that changes in expected excess returns are highly persistent, so that modest movements in short-run expected returns are capitalized into large changes in stock prices. The persistence of expected returns arises largely from the persistence of the dividend-price ratio, one of the main forecasting variables for excess stock returns.

Table II

VAR Coefficient Estimates

This table reports coefficient estimates for a monthly 1-lag VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, log dividend-price ratio, and relative bill rate (the difference between the bill rate and a 1-year backwards moving average). The excess stock return is measured in % per month, while the remaining variables are in % per year.

		e_t	r_t	$\Delta y_{1,t}$	$s_{n,t}$	$d_t - p_t$	rb_t
	e_{t+1}	-0.010	0.027	-0.666	0.336	0.363	-0.339
		(0.056)	(0.061)	(0.388)	(0.237)	(0.213)	(0.277)
	r_{t+1}	-0.049	0.431	0.362	0.210	0.262	0.163
		(0.037)	(0.070)	(0.273)	(0.155)	(0.186)	(0.197)
	$\Delta y_{1,t+1}$	0.015	-0.017	0.060	0.078	-0.075	-0.011
		(0.011)	(0.012)	(0.104)	(0.040)	(0.045)	(0.060)
1952:1–1987:2	$s_{n,t+1}$	-0.005	0.010	-0.041	0.860	0.053	-0.016
		(0.009)	(0.011)	(0.085)	(0.037)	(0.037)	(0.055)
	$d_{t+1} - p_{t+1}$	-0.041	-0.001	0.002	0.004	0.999	0.008
		(0.001)	(0.001)	(0.006)	(0.003)	(0.004)	(0.004)
	rb_{t+1}	0.016	-0.016	0.090	0.103	-0.079	0.889
		(0.011)	(0.012)	(0.102)	(0.039)	(0.044)	(0.058)
		e_t	r_t	$\Delta y_{1,t}$	$s_{n,t}$	$d_t - p_t$	rb_t
	e_{t+1}	-0.003	0.138	-1.503	0.504	0.594	-0.287
		(0.064)	(0.086)	(0.731)	(0.307)	(0.233)	(0.369)
	r_{t+1}	0.022	0.151	-0.300	-0.209	-0.415	0.058
		(0.040)	(0.077)	(0.363)	(0.204)	(0.223)	(0.281)
	$\Delta y_{1,t+1}$	0.016	-0.007	-0.196	0.107	-0.041	0.123
		(0.008)	(0.012)	(0.105)	(0.042)	(0.026)	(0.052)
1952:1–1979:9	$s_{n,t+1}$	-0.007	0.001	0.208	0.858	0.025	-0.139
		(0.008)	(0.001)	(0.097)	(0.038)	(0.026)	(0.049)
	$d_{t+1} - p_{t+1}$	-0.040	-0.000	-0.006	0.006	1.001	0.009
		(0.001)	(0.001)	(0.014)	(0.005)	(0.004)	(0.006)
	rb_{t+1}	0.015	-0.004	-0.153	0.137	-0.044	1.012
		(0.008)	(0.011)	(0.102)	(0.041)	(0.026)	(0.051)
		e_t	r_t	$\Delta y_{1,t}$	$s_{n,t}$	$d_t - p_t$	rb_t
	e_{t+1}	0.045	0.128	-0.003	0.681	0.509	-0.460
		(0.072)	(0.094)	(0.696)	(0.398)	(0.244)	(0.420)
	r_{t+1}	0.034	0.001	-0.665	-0.253	-0.239	0.679
		(0.041)	(0.063)	(0.415)	(0.251)	(0.300)	(0.288)
	$\Delta y_{1,t+1}$	0.014	-0.014	-0.104	0.127	-0.042	0.105
		(0.006)	(0.006)	(0.068)	(0.039)	(0.021)	(0.052)
1952:1–1972:12	$s_{n,t+1}$	-0.004	0.008	0.137	0.824	0.016	-0.136
		(0.006)	(0.007)	(0.070)	(0.040)	(0.021)	(0.049)
	$d_{t+1} - p_{t+1}$	-0.035	-0.000	0.001	-0.001	0.997	0.006
		(0.001)	(0.002)	(0.009)	(0.005)	(0.005)	(0.005)
	rb_{t+1}	0.014	-0.012	-0.060	0.157	-0.042	1.001
		(0.006)	(0.006)	(0.068)	(0.039)	(0.021)	(0.051)

Table II—*Continued*

		e_t	r_t	$\Delta y_{1,t}$	$s_{n,t}$	$d_t - p_t$	rb_t
	e_{t+1}	−0.096	−0.030	−0.791	0.540	1.151	−0.117
		(0.082)	(0.089)	(0.417)	(0.323)	(0.517)	(0.372)
	r_{t+1}	−0.121	0.653	0.771	0.247	0.783	0.102
		(0.052)	(0.082)	(0.259)	(0.203)	(0.414)	(0.211)
	$\Delta y_{1,t+1}$	0.018	−0.016	0.089	0.040	−0.171	−0.064
		(0.021)	(0.020)	(0.120)	(0.059)	(0.103)	(0.078)
1973:1–1987:2	$s_{n,t+1}$	−0.006	0.009	−0.074	0.881	0.115	0.025
		(0.017)	(0.018)	(0.099)	(0.055)	(0.086)	(0.073)
	$d_{t+1} - p_{t+1}$	−0.046	−0.001	0.005	0.005	1.002	0.006
		(0.001)	(0.001)	(0.006)	(0.004)	(0.008)	(0.005)
	rb_{t+1}	0.019	−0.015	0.115	0.065	−0.171	0.837
		(0.021)	(0.020)	(0.119)	(0.058)	(0.100)	(0.075)

The importance of the dividend-price ratio could give rise to another concern about the VAR results. If the dividend-price ratio is an important return forecasting variable, then innovations in return forecasts are highly correlated with innovations in the dividend-price ratio. But since dividends are smooth, innovations in the dividend-price ratio are highly correlated with stock returns themselves. This suggests that a regression of the stock return $\tilde{e}$ on the return news component $\tilde{e}_e$ is likely to have a high R^2 whether return news is highly variable or not.[10]

There are two responses to this concern. First, this effect would not be present if dividend news were the only force driving stock returns; for then the dividend-price ratio would not forecast stock returns. Thus at worst this effect can only amplify the importance of return news for the stock market. Second, the effect is only important for the simple regression of stock returns on return news. It does not distort the direct calculation of the variance of return news as reported in the top panel of Table III.

Our VAR results may also seem surprising because they contrast strongly with the results of Kothari and Shanken (1992). Kothari and Shanken regress annual stock returns on current and future annual dividend growth over the period 1926–88, and find that they can explain half the variance of stock returns with these variables. This suggests a greater role for dividend news than we have found in Table III.

We attribute the difference in results to several factors. First, Kothari and Shanken study a longer sample period. Campbell (1991) uses the VAR method to study their sample period and also finds a greater role for dividend news in 1926–88 and particularly 1926–51 than in the period 1952–88 studied here. When we run Kothari and Shanken's regression over our sample period, we find that the R^2 falls from 56% to 39%, which is consistent with the pattern of the VAR results.

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[10] Collins, Kothari, Shanken, and Sloan (1992) mention this point.

Table III
Variance Decomposition for Excess Stock Returns

This table is based on a monthly VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, log dividend-price ratio, and relative bill rate (the difference between the bill rate and a 1-year backwards moving average). "Return R^2" is the R^2 in the regression of the excess stock return on the VAR explanatory variables, while "Significance" is the joint significance of the explanatory variables in this regression. The VAR is used to calculate the components of the unexpected excess stock return $\tilde{e}_{t+1}$ in equation (2), $\tilde{e}_{t+1} = \tilde{e}_{d,t+1} - \tilde{e}_{r,t+1} - \tilde{e}_{e,t+1}$. The component $\tilde{e}_{d,t+1}$ can be interpreted as news about future dividends, while $\tilde{e}_{r,t+1}$ is news about future real interest rates and $\tilde{e}_{e,t+1}$ is news about future excess stock returns. The table reports the variances and covariances of these components, divided by the variance of $\tilde{e}_{t+1}$ so that the numbers reported add up to one. The bottom panel gives the implied R^2 statistics from simple regressions of $\tilde{e}_{t+1}$ on each component. Asymptotic standard errors are reported in parentheses below each statistic in the table.

| VAR lag length | 1 | 1 | 1 | 1 | 3 |
Sample period	52:1–87:2	52:1–79:9	52:1–72:12	73:1–87:2	52:1–87:2
Return R^2	0.073	0.097	0.062	0.131	0.122
Significance	0.000	0.000	0.010	0.000	0.000
Shares of					
$\text{Var}(\tilde{e}_d)$	0.146	0.153	0.189	0.137	0.097
	(0.039)	(0.048)	(0.093)	(0.053)	(0.026)
$-2\,\text{Cov}(\tilde{e}_d, \tilde{e}_r)$	−0.015	−0.023	−0.029	−0.062	−0.020
	(0.016)	(0.035)	(0.035)	(0.053)	(0.022)
$-2\,\text{Cov}(\tilde{e}_d, \tilde{e}_e)$	0.072	0.100	0.317	−0.309	0.062
	(0.175)	(0.256)	(0.182)	(0.280)	(0.134)
$\text{Var}(\tilde{e}_r)$	0.013	0.012	0.006	0.032	0.023
	(0.004)	(0.008)	(0.004)	(0.018)	(0.009)
$2\,\text{Cov}(\tilde{e}_r, \tilde{e}_e)$	0.079	−0.139	−0.068	0.188	0.101
	(0.060)	(0.085)	(0.051)	(0.146)	(0.072)
$\text{Var}(\tilde{e}_e)$	0.705	0.897	0.585	1.013	0.736
	(0.184)	(0.269)	(0.243)	(0.210)	(0.134)
$R^2(\tilde{e}_d)$	0.209	0.240	0.587	0.017	0.144
	(0.226)	(0.279)	(0.247)	(0.071)	(0.173)
$R^2(\tilde{e}_r)$	0.160	0.402	0.296	0.282	0.177
	(0.185)	(0.184)	(0.207)	(0.216)	(0.165)
$R^2(\tilde{e}_e)$	0.864	0.859	0.861	0.896	0.909
	(0.024)	(0.018)	(0.019)	(0.020)	(0.021)

Second, Kothari and Shanken study annual rather than monthly stock returns. Variation in expected returns causes transitory variation in stock prices while dividend news causes permanent variation in stock prices; hence one would expect that dividend news becomes more important as one measures returns over longer time intervals. To investigate this possibility, we ran a quarterly version of our VAR model over the period 1952–88 and found that the variance of quarterly dividend news is 39% of the variance of quarterly unexpected stock returns.[11] An annual version of our model over 1952–88

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[11] The variance of expected return news does not fall in our quarterly model; the increase in dividend news variance is instead accommodated by the covariance term between dividend news and expected return news.

gives results closer to our monthly results, but with only 35 annual observations there may be a problem of overfitting in the stock return forecasting equation. We interpret these findings as mildly supportive of the importance of the measurement interval in decomposing return variation.

A third reason for the difference between our results and those of Kothari and Shanken is that, as Kothari and Shanken recognize, correlation between dividend news and return news can give their regression a high R^2 statistic even if dividend news is not highly variable. The correlation between the two news components is weak in the period studied in this paper, but Campbell (1991) reports a much stronger correlation in the 1926–88 and particularly the 1926–51 period.

Our discussion so far has placed little emphasis on news about real interest rates because this plays a relatively minor role in the variance decomposition for stock returns. Even though there is some evidence that ex ante real interest rates vary through time, this variation is largely transitory and does not cumulate over time. Thus the variance of real interest rate news remains small and precisely estimated in all our sample periods. There is however an imprecisely estimated covariance between real interest rate news and excess return news (negative in the earlier subsamples, positive in the later ones). This covariance is attributed to the independent variable in a simple regression of unexpected stock returns on real interest rate news, so the simple regression R^2 for real interest rate news is quite large in some subsamples.

C. A Variance Decomposition for Excess Bond Returns

Table IV presents a VAR analysis of excess bond returns. The results have some similarities with the results for stock returns, but also some interesting differences. The monthly forecastability of excess bond returns is slightly less than the forecastability of stock returns, but it changes through time in a similar way; the R^2 increases from 5% in the 1952–72 period to 9% in the 1973–87 period, while the joint significance of the forecasting variables moves from 2.7% to 1.4%.

In the earlier subperiods 1952–79 and 1952–72, the variance decomposition for bond returns can be described very simply. Almost all the variation in bond returns over this period can be accounted for by news about future inflation, while the other components are small and imprecisely estimated. The variance of inflation news is insignificantly different from the variance of unexpected excess bond returns, and a simple regression of bond returns on inflation news yields an R^2 insignificantly different from one. This decomposition is consistent with the results of Fama (1975, 1976, 1990b) and Mishkin (1990) on the ability of interest rates to forecast future inflation over both short and long horizons.

In the sample periods that include 1980s data, the story is somewhat more complicated. Inflation news still has roughly the same variance as the overall variance of bond returns. But now news about future excess bond returns contributes roughly the same variance again. This does not increase the overall variance of bond returns, however, because the excess return news

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Table IV

Variance Decomposition for Excess Bond Returns

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This table is based on a monthly VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, log dividend-price ratio, and relative bill rate (the difference between the bill rate and a 1-year backwards moving average). "Return R^2" is the implied R^2 in a regression of the excess bond return on the VAR explanatory variables, while "Significance" is the joint significance of the explanatory variables in this regression. The VAR is used to calculate the components of the unexpected bond return $\tilde{x}_{t+1}$ in equation (3), $\tilde{x}_{t+1} = -\tilde{x}_{\pi,t+1} - \tilde{x}_{r,t+1} - \tilde{x}_{x,t+1}$. The component $\tilde{x}_{\pi,t+1}$ can be interpreted as news about future inflation, while $\tilde{x}_{r,t+1}$ is news about future real interest rates and $\tilde{x}_{x,t+1}$ is news about future excess bond returns. The table reports the variances and covariances of these components, divided by the variance of $\tilde{x}_{t+1}$ so that the numbers reported add up to one. The bottom panel of the table gives the implied R^2 statistics from simple regressions of $\tilde{x}_{t+1}$ on each component. Asymptotic standard errors are reported in parentheses below each statistic in the table.

VAR lag length	1	1	1	1	3
Sample period	52:1–87:2	52:1–79:9	52:1–72:12	73:1–87:2	52:1–87:2
Return R^2	0.071	0.052	0.053	0.086	0.117
Significance	0.000	0.006	0.027	0.014	0.000
Shares of					
$\text{Var}(\tilde{x}_\pi)$	1.084	1.116	0.757	1.188	1.476
	(0.330)	(0.298)	(0.251)	(0.484)	(0.616)
$2\,\text{Cov}(\tilde{x}_\pi, \tilde{x}_r)$	−0.116	−0.068	0.054	−0.204	−0.198
	(0.068)	(0.130)	(0.056)	(0.157)	(0.149)
$2\,\text{Cov}(\tilde{x}_\pi, \tilde{x}_x)$	−1.105	−0.341	−0.168	−1.423	−1.750
	(0.623)	(0.439)	(0.362)	(1.062)	(1.108)
$\text{Var}(\tilde{x}_r)$	0.023	0.050	0.022	0.040	0.043
	(0.008)	(0.037)	(0.017)	(0.024)	(0.019)
$2\,\text{Cov}(\tilde{x}_r, \tilde{x}_x)$	0.151	−0.143	−0.089	0.234	0.241
	(0.098)	(0.145)	(0.047)	(0.210)	(0.172)
$\text{Var}(\tilde{x}_x)$	0.962	0.386	0.425	1.165	1.188
	(0.368)	(0.272)	(0.279)	(0.631)	(0.581)
$R^2(\tilde{x}_\pi)$	0.207	0.744	0.647	0.118	0.170
	(0.183)	(0.188)	(0.228)	(0.198)	(0.190)
$R^2(\tilde{x}_r)$	0.072	0.062	0.001	0.075	0.097
	(0.103)	(0.065)	(0.013)	(0.139)	(0.150)
$R^2(\tilde{x}_x)$	0.245	0.054	0.206	0.280	0.158
	(0.105)	(0.095)	(0.160)	(0.151)	(0.143)

and the inflation news are negatively correlated. When investors learn that long-run inflation will be higher than they expected, they also tend to learn that excess bond returns will be lower than they expected. This covariance has the effect of decreasing bond price variability because the capital loss from higher expected inflation is partly offset by a capital gain from lower expected excess bond returns. Once one adds the variance of inflation news, the variance of excess bond return news, and twice the covariance between them, the overall variance of bond returns is roughly equal to the variance of

either of its two major components. Real interest rate news again plays a minor role in the variance decomposition.

D. A Covariance Decomposition for Excess Bond and Stock Returns

In Tables V and VI we study the determinants of the covariance between excess stock and bond returns. Table V reports the correlation matrix of the return components $\tilde{e}_d$, $\tilde{e}_r$, $\tilde{e}_e$, $\tilde{x}_\pi$, $\tilde{x}_r$, and $\tilde{x}_x$, estimated from a 1-lag VAR over the full sample and each of our subsamples. The three elements at the top left of each correlation matrix are the correlations among stock return components, while the three elements at the bottom right are correlations among bond return components. The table confirms some of the points made above; in particular, the negative correlation between inflation news $\tilde{x}_\pi$ and excess bond return news $\tilde{x}_x$ shows up clearly in the later subsamples.

The remaining elements of each correlation matrix are the cross correlations between stock return and bond return components. There are three main points to emphasize. First, news about excess stock returns $\tilde{e}_e$ and news about excess bond returns $\tilde{x}_x$ have correlations above 0.8 in every subsample. This strong correlation is due to the fact that similar variables, notably the long-short yield spread, forecast both bond and stock returns. Fama and French (1989) also emphasize the common movement in return forecasts for different long-term assets. Second, the real interest rate news relevant for stocks $\tilde{e}_r$ and the real interest rate news relevant for bonds $\tilde{x}_r$ have correlations above 0.65 in every subsample. This should not be surprising, since both $\tilde{e}_r$ and $\tilde{x}_r$ are made up of the same real interest rate forecasts, differing only in the horizon and weighting scheme. Third, there is a negative correlation between news about excess stock returns $\tilde{e}_e$ and news about future inflation $\tilde{x}_\pi$. This correlation, which is -0.5 in the 1952–72 period and -0.6 in the 1973–87 period, is due to the fact that short-term nominal interest rates forecast both higher inflation and lower stock returns (Fama and Schwert (1977)).

Table VI develops the implications of these correlations for the covariance between stock return innovations $\tilde{e}$ and bond return innovations $\tilde{x}$. The first row of Table VI gives the sample covariance itself, as reported earlier in Table I. This covariance rises from the earlier part of the sample to the later part of the sample, both because the bond return variance increases and because the correlation between bond and stock returns increases. The lower panels of Table VI show the covariance of $\tilde{e}$ with each of the components of $\tilde{x}$, and the covariance of $\tilde{x}$ with each of the components of $\tilde{e}$. Thus Table VI answers the question, "What would be the covariance of bond and stock returns if one of these asset returns consisted of a single component while the other return were as measured in the data?".

Table VI shows that the covariance between excess stock and bond returns is determined by the balance between several offsetting effects. First, stock and bond returns tend to move in opposite directions when expected inflation varies; an increase in long-run expected inflation is bad news for the bond

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Table V

Correlations of Components of Bond and Stock Returns

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This table is based on a monthly 1-lag VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, log dividend-price ratio, and relative bill rate (the difference between the bill rate and a 1-year backwards moving average). The VAR is used to calculate the components of the unexpected excess stock return $\tilde{e}_{t+1}$ in equation (2), $\tilde{e}_{t+1} = \tilde{e}_{d,t+1} - \tilde{e}_{r,t+1} - \tilde{e}_{e,t+1}$. The component $\tilde{e}_{d,t+1}$ can be interpreted as news about future dividends, while $\tilde{e}_{r,t+1}$ is news about future real interest rates and $\tilde{e}_{e,t+1}$ is news about future excess stock returns. The VAR is also used to calculate the components of the unexpected bond return $\tilde{x}_{t+1}$ in equation (3), $\tilde{x}_{t+1} = -\tilde{x}_{\pi,t+1} - \tilde{x}_{r,t+1} - \tilde{x}_{x,t+1}$. The component $\tilde{x}_{\pi,t+1}$ can be interpreted as news about future inflation, while $\tilde{x}_{r,t+1}$ is news about future real interest rates and $\tilde{x}_{x,t+1}$ is news about future excess bond returns. The table reports the correlations of these components, with asymptotic standard errors in parentheses.

		$\tilde{e}_r$	$\tilde{e}_e$	$\tilde{x}_\pi$	$\tilde{x}_r$	$\tilde{x}_x$
	$\tilde{e}_d$	0.169	−0.112	−0.047	0.020	0.071
		(0.186)	(0.278)	(0.184)	(0.295)	(0.263)
	$\tilde{e}_r$	1.000	0.419	−0.304	0.845	0.481
			(0.268)	(0.170)	(0.052)	(0.224)
	$\tilde{e}_e$		1.000	−0.649	0.756	0.816
1952:1–1987:2				(0.225)	(0.188)	(0.171)
	$\tilde{x}_\pi$			1.000	−0.365	−0.541
					(0.168)	(0.144)
	$\tilde{x}_r$				1.000	0.506
						(0.230)
		$\tilde{e}_r$	$\tilde{e}_e$	$\tilde{x}_\pi$	$\tilde{x}_r$	$\tilde{x}_x$
	$\tilde{e}_d$	0.273	−0.135	−0.076	0.237	−0.026
		(0.328)	(0.350)	(0.158)	(0.403)	(0.333)
	$\tilde{e}_r$	1.000	−0.672	−0.053	0.862	−0.499
			(0.190)	(0.263)	(0.090)	(0.341)
	$\tilde{e}_e$		1.000	−0.273	−0.924	0.843
1952:1–1979:9				(0.282)	(0.085)	(0.229)
	$\tilde{x}_\pi$			1.000	−0.145	−0.260
					(0.259)	(0.248)
	$\tilde{x}_r$				1.000	−0.514
						(0.343)
		$\tilde{e}_r$	$\tilde{e}_e$	$\tilde{x}_\pi$	$\tilde{x}_r$	$\tilde{x}_x$
	$\tilde{e}_d$	0.426	−0.477	0.186	0.525	−0.466
		(0.305)	(0.260)	(0.171)	(0.300)	(0.270)
	$\tilde{e}_r$	1.000	−0.572	0.324	0.658	−0.445
			(0.249)	(0.207)	(0.248)	(0.311)
	$\tilde{e}_8$ie		1.000	−0.498	−0.954	0.847
1952:1–1972:12				(0.236)	(0.132)	(0.146)
	$\tilde{x}_\pi$			1.000	0.212	−0.148
					(0.221)	(0.271)
	$\tilde{x}_r$				1.000	−0.464
						(0.319)

market but good news for the stock market. This effect by itself would lead to a large negative covariance between bond and stock returns. It shows up in the negative correlation between $\tilde{e}_e$ and $\tilde{x}_\pi$ in Table V, and in the positive covariance between $\tilde{e}$ and $\tilde{x}_\pi$ in Table VI. (Recall that $\tilde{e}_e$ and $\tilde{x}_\pi$ affect $\tilde{e}$ and

Table V—*Continued*

		$\tilde{e}_r$	$\tilde{e}_e$	$\tilde{x}_\pi$	$\tilde{x}_r$	$\tilde{x}_x$
	$\tilde{e}_d$	0.468	0.414	−0.340	0.471	0.498
		(0.236)	(0.274)	(0.189)	(0.283)	(0.239)
	$\tilde{e}_r$	1.000	0.522	−0.443	0.954	0.537
			(0.282)	(0.245)	(0.025)	(0.320)
	$\tilde{e}_e$		1.000	−0.636	0.705	0.804
1973:1–1987:2				(0.261)	(0.230)	(0.193)
	$\tilde{x}_\pi$			1.000	−0.469	−0.605
					(0.239)	(0.191)
	$\tilde{x}_r$				1.000	0.542
						(0.329)

Table VI

Covariance Decomposition for Bond and Stock Returns

This table is based on a monthly VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, log dividend-price ratio, and relative bill rate (the difference between the bill rate and a 1-year backwards moving average). The VAR is used to calculate the components of the unexpected excess stock return $\tilde{e}_{t+1}$ in equation (2), $\tilde{e}_{t+1} = \tilde{e}_{d,t+1} - \tilde{e}_{r,t+1} - \tilde{e}_{e,t+1}$. The component $\tilde{e}_{d,t+1}$ can be interpreted as news about future dividends, while $\tilde{e}_{r,t+1}$ is news about future real interest rates and $\tilde{e}_{e,t+1}$ is news about future excess stock returns. The VAR is also used to calculate the components of the unexpected bond return $\tilde{x}_{t+1}$ in equation (3), $\tilde{x}_{t+1} = -\tilde{x}_{\pi,t+1} - \tilde{x}_{r,t+1} - \tilde{x}_{x,t+1}$. The component $\tilde{x}_{\pi,t+1}$ can be interpreted as news about future inflation, while $\tilde{x}_{r,t+1}$ is news about future real interest rates and $\tilde{x}_{x,t+1}$ is news about future excess bond returns. The table reports the covariance of the unexpected stock (bond) return with the components of the unexpected bond (stock) return. Asymptotic standard errors are given in parentheses.

VAR lag length Sample period	1 52:1–87:2	1 52:1–79:9	1 52:1–72:12	1 73:1–87:2	3 52:1–87:2
$\text{Cov}(\tilde{e}, \tilde{x})$	2.310	0.689	0.536	4.655	2.089
$\text{Cov}(\tilde{e}, \tilde{x}_\pi)$	6.693	1.773	2.458	11.318	7.830
	(3.060)	(2.024)	(1.281)	(5.752)	(2.962)
$\text{Cov}(\tilde{e}, \tilde{x}_r)$	−0.843	0.936	0.495	−2.077	−1.114
	(0.575)	(0.632)	(0.430)	(1.336)	(0.665)
$\text{Cov}(\tilde{e}, \tilde{x}_x)$	−8.160	−3.398	−3.489	−13.896	−8.805
	(2.918)	(1.895)	(1.421)	(4.993)	(2.721)
$\text{Cov}(\tilde{x}, \tilde{e}_d)$	−0.106	0.170	0.287	−1.667	−0.039
	(0.884)	(0.505)	(0.571)	(1.902)	(0.927)
$\text{Cov}(\tilde{x}, \tilde{e}_r)$	−0.321	0.188	−0.022	−0.842	−0.461
	(0.302)	(0.147)	(0.122)	(1.027)	(0.480)
$\text{Cov}(\tilde{x}, \tilde{e}_e)$	−2.095	−0.707	−0.227	−5.480	−1.667
	(1.126)	(0.699)	(0.690)	(2.293)	(1.106)

$\tilde{x}$ negatively.) Second, in the later part of our sample period 1973–87, stock and bond returns tend to move in the same direction when real interest rates change. This effect by itself would lead to a small positive covariance between bond and stock returns in the 1973–87 period. It shows up in the positive

correlation of $\tilde{e}_e$ and $\tilde{x}_r$ in Table V for 1973–87, and in the negative covariance between $\tilde{e}$ and $\tilde{x}_r$ in Table VI for the same sample period. Third, stock and bond returns move in the same direction when expected future excess returns vary. This effect by itself would lead to a large positive covariance between bond and stock returns. It shows up in the positive correlation of $\tilde{e}_e$ and $\tilde{x}_x$ in Table V, and in the negative covariance of $\tilde{e}$ and $\tilde{x}_x$ in Table VI.

Combining all three effects, we obtain a small positive covariance between the two long-term asset returns. This overall covariance increases as one moves from the earlier subsamples to the later ones because the real interest rate and expected excess return effects become stronger relative to the inflation effect.

Our finding of a positive association between stock returns and inflation news may at first seem surprising. Fama and Schwert (1977) and many subsequent authors have argued that inflation news is bad for the stock market. In fact, however, our finding is not inconsistent with the previous literature. The main result in that literature is that expected inflation (usually proxied by a short-term nominal interest rate) forecasts low stock returns. Our VAR system also gives this result. Fama and Schwert's evidence for a negative correlation between inflation innovations and stock return innovations is much weaker; and our definition of inflation news is not the contemporaneous innovation in inflation, but the revision in long-run expectations of inflation from 2 months ahead to 10 years ahead. This can have a positive correlation with stock returns even if contemporaneous inflation has a weak negative correlation with stock returns.[12]

E. Variance Decompositions for Short-Rate and Yield Spread Innovations

Further insight into these results can be gained from Tables VII and VIII, which decompose the innovation variances of short rates and long-short yield spreads. The one-month bill rate has only two components: news about inflation one month ahead, and news about the real interest rate one month ahead. Table VII shows that these two components have a strong tendency to offset each other. The variances of both news components exceed the variance of short rate innovation, but they have a large negative covariance. This reflects the fact that short-run forecasts of inflation and real interest rates are negatively correlated. A positive innovation in expected inflation tends to be associated with a negative innovation in the expected real interest rate, so that the effect on the short-term nominal interest rate is dampened.

Table VII also illustrates the point, discussed as a theoretical possibility in Section I.D, that a variable component of an asset return can have almost no explanatory power in a simple regression of the return on that component. According to Table VII, short-term real interest rate variation is important

[12] In our monthly data the correlation between contemporaneous inflation and stock returns is small and negative at -0.080 in 1952–72 and -0.075 in 1952–88. The correlation is again negative, and somewhat larger in absolute value, in quarterly data.

Table VII

Variance Decomposition for Short-Rate Innovations

This table is based on a monthly VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, log dividend-price ratio, and relative bill rate (the difference between the bill rate and a 1-year backwards moving average). "Return R^2" is the implied R^2 in a regression of the excess return on a "level portfolio" of 2-month bills on the VAR explanatory variables, while "Significance" is the joint significance of the explanatory variables in this regression. The VAR is used to calculate the components of the 1-month bill rate innovation $\tilde{y}_{1,t+1}$ in equation (7), $\tilde{y}_{1,t+1} = \tilde{y}_{\pi,t+1} + \tilde{y}_{r,t+1}$. The component $\tilde{y}_{\pi,t+1}$ can be interpreted as news about future inflation, while $\tilde{y}_{r,t+1}$ is news about future real interest rates. The table reports the variances and covariances of these components, divided by the variance of $\tilde{y}_{1,t+1}$ so that the numbers reported add up to one. The bottom panel of the table gives the implied R^2 statistics from simple regressions of $\tilde{y}_{1,t+1}$ on each component. Asymptotic standard errors are reported in parentheses below each statistic in the table.

VAR lag length	1	1	1	1	3
Sample period	52:1–87:2	52:1–79:9	52:1–72:12	73:1–87:2	52:1–87:2
Shares of					
$\text{Var}(\tilde{y}_\pi)$	4.640	2.473	0.868	4.928	3.317
	(1.445)	(1.376)	(0.678)	(1.287)	(1.254)
$2\,\text{Cov}(\tilde{y}_\pi, \tilde{y}_r)$	−7.484	−2.630	−0.067	−8.238	−4.837
	(2.748)	(2.374)	(0.806)	(2.374)	(2.305)
$\text{Var}(\tilde{y}_r)$	3.843	1.157	0.199	4.311	2.520
	(1.348)	(1.085)	(0.375)	(1.138)	(1.108)
$R^2(\tilde{y}_\pi)$	0.174	0.542	0.802	0.133	0.243
	(0.078)	(0.225)	(0.403)	(0.074)	(0.106)
$R^2(\tilde{y}_r)$	0.003	0.022	0.138	0.008	0.004
	(0.012)	(0.096)	(0.745)	(0.022)	(0.018)

and tends to offset short-term variation in inflation, but because inflation news dominates the behavior of the short rate the explanatory power of real interest rate news in a simple regression is negligible.

The pattern of results in Table VII is very striking, but for two reasons it should be interpreted with some caution. First, in the earlier subsamples 1952–79 and 1952–72 the real interest rate terms are not significantly different from zero and the variance share of inflation news is not significantly different from one. This reflects the weak forecastability of ex post real interest rates in this period. Second, forecastable measurement error in inflation might create the pattern of results in Table VII even in a world in which true real interest rates were constant. Measurement error is unlikely to be the whole explanation, however, as numerous authors have recorded the opposing low-frequency movements of inflation and real interest rates in the late 1970s and early 1980s. (See for example Fama (1990b)).

Table VIII gives a variance decomposition for the long-short yield spread. Here again we find an important role for forecasts of both inflation and real interest rates, now measured as changes from a one-month horizon to a ten-year horizon. Just as in Table VII, innovations in these forecasts of inflation and real interest rates have a tendency to offset each other. Each

Table VIII

Variance Decomposition for Yield Spread Innovations

This table is based on a monthly VAR that includes the excess stock return, real interest rate, change in the 1-month bill rate, 10-year and 2-month yield spreads, and the relative bill rate (the difference between the bill rate and a 1-year backwards moving average). "Return R^2" is the implied R^2 in a regression of the excess return on a "slope portfolio", long 10-year bonds and short 2-month bills, on the VAR explanatory variables, while "Significance" is the joint significance of the explanatory variables in this regression. The VAR is used to calculate the components of the unexpected slope portfolio return $\tilde{s}_{t+1}$ in equation (8), $\tilde{s}_{t+1} = \tilde{s}_{\pi,t+1} + \tilde{s}_{r,t+1} + \tilde{s}_{x,t+1}$. The component $\tilde{s}_{\pi,t+1}$ can be interpreted as news about future inflation, while $\tilde{s}_{r,t+1}$ is news about future real interest rates and $\tilde{s}_{x,t+1}$ is news about future excess bond returns. The table reports the variances and covariances of these components, divided by the variance of $\tilde{s}_{t+1}$ so that the numbers reported add up to one. The bottom panel gives the implied R^2 statistics from simple regressions of $\tilde{s}_{t+1}$ on each component. Asymptotic standard errors are reported in parentheses below each statistic in the table.

| VAR lag length | 1 | 1 | 1 | 1 | 3 |
Sample period	52:1–87:2	52:1–79:9	52:1–72:12	73:1–87:2	52:1–87:2
Shares of					
$\mathrm{Var}(\tilde{s}_\pi)$	4.864	2.215	0.837	5.096	2.885
	(1.550)	(1.442)	(0.772)	(1.233)	(1.318)
$2\,\mathrm{Cov}(\tilde{s}_\pi, \tilde{s}_r)$	−8.851	−2.685	−0.181	−9.679	−5.243
	(3.082)	(2.512)	(0.966)	(2.488)	(2.549)
$2\,\mathrm{Cov}(\tilde{s}_\pi, \tilde{s}_x)$	0.303	0.027	−0.312	0.619	−0.030
	(0.468)	(0.451)	(0.259)	(0.606)	(0.573)
$\mathrm{Var}(\tilde{s}_r)$	4.664	1.213	0.179	5.265	3.051
	(1.581)	(1.171)	(0.359)	(1.321)	(1.309)
$2\,\mathrm{Cov}(\tilde{s}_r, \tilde{s}_x)$	−0.247	0.130	0.312	−0.598	0.027
	(0.340)	(0.307)	(0.338)	(0.596)	(0.451)
$\mathrm{Var}(\tilde{s}_x)$	0.267	0.100	0.163	0.297	0.356
	(0.110)	(0.074)	(0.113)	(0.171)	(0.183)
$R^2(\tilde{s}_\pi)$	0.072	0.354	0.417	0.063	0.021
	(0.056)	(0.225)	(0.486)	(0.061)	(0.047)
$R^2(\tilde{s}_r)$	0.003	0.003	0.334	0.003	0.052
	(0.011)	(0.036)	(1.018)	(0.012)	(0.064)
$R^2(\tilde{s}_x)$	0.325	0.319	0.165	0.319	0.353
	(0.226)	(0.379)	(0.236)	(0.265)	(0.227)

considered in isolation implies a more variable yield spread than we observe, but they have a strong negative covariance which tends to reduce the variability of the yield spread.

It may seem puzzling that real interest rate variation plays an important role for both short rates and yield spreads but is much less important for the excess bond return. The reason is that VAR forecasts of the real interest rate have the mean-reverting property that short-run real interest rate forecasts are more variable than long-run forecasts. An increase in the expected short-run real interest rate 1 month ahead is associated with expected decreases in real interest rates between 1 month ahead and 10 years ahead as the expected real interest rate returns to its long-run average level. Thus the real interest rate components of the short rate and the yield spread are

negatively correlated and tend to cancel out when they are added together in the real interest rate component of the excess bond return.

Tables VII and VIII also clarify the role of changing expected excess bond returns, or term premiums, in the term structure of interest rates. Recall that Table IV showed a negative correlation between long-run expected inflation and term premiums, helping to dampen the variability of excess bond returns. This effect was particularly strong in the later part of our sample period. Table VIII shows that over the full sample and the 1973–87 subsample, the covariance between inflation and expected bond returns acts to increase the innovation variance of the yield spread. The result in Table VIII is consistent with the result in Table IV because VAR forecasts of inflation rates also display some mean-reversion, albeit weaker than in the case of real interest rates. A 1% increase in expected inflation over a 10-year horizon is typically associated with a greater than 1% increase in expected inflation 1 month ahead, so that expected inflation rates fall between the 1-month and 10-year horizons. This by itself lowers the yield spread; at the same time the term premium falls, further decreasing the spread. Campbell and Shiller (1991) also found that changing term premia amplify variations in the long-short yield spread.

III. Conclusions

In this paper we have used a dynamic accounting framework and time-series econometric methods to break excess returns on long-term assets into components associated with news about future cash flows and discount rates. Since we use an accounting framework rather than a behavioral model, we are able to make statements only about proximate causes rather than fundamental causes of asset price movements. Nevertheless, our empirical results shed light on several issues that have been debated in the finance literature during the last ten years.

Our first important finding is that a large part of the variance of excess stock returns is attributable to changing expectations of future excess stock returns. The postwar U.S. stock market displays "excess volatility" in the sense that returns have a standard deviation two or three times greater than the standard deviation of news about future dividend growth. We obtain this result by calculating the implications of a return forecasting equation, making no assumptions about the dividend process; news about dividends is treated as a residual component of the stock return. At a mechanical level, the result comes from the fact that our forecasts of excess stock returns are highly persistent, so that small changes in forecast monthly returns cumulate over time and have a big effect on the stock price.[13]

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[13] This is related to the fact that long-horizon excess stock returns are more highly forecastable than short-horizon excess returns (Fama and French 1988a, 1988b). Campbell (1991) and Kandel and Stambaugh (1988) explore the implications of a VAR forecasting system for long-horizon forecastability of returns.

An important unanswered question is what economic forces create these persistent changes in expected excess stock returns. Our second finding is that these changes are not associated with important changes in long-horizon forecasts of real interest rates. The real interest rate component of the excess stock return has a much smaller variance than the other components. This suggests that theoretical models of stock market pricing should not rely heavily on changing real interest rates. Homoskedastic asset-pricing models tend to generate large variations in real interest rates and small variations in equity risk premiums; the opposite pattern is needed to fit the data.

A similar point can be made for bond returns. The theoretical finance literature contains numerous pricing models for real bonds, and these are sometimes applied to data on the nominal term structure (Gibbons (1989), Gibbons and Ramaswamy (1992)). But we find that the variance of excess returns on long-term nominal bonds is accounted for primarily by news about future inflation rates, which would have no impact if bonds had real payoffs. Real bond-pricing models cannot be applied to the nominal term structure unless the price of inflation risk is exactly zero; if the inflation risk price is even slightly positive or negative, the inflation risk premium will be large and will tend to dominate the pricing of nominal bonds.[14]

Although long-horizon forecasts of real interest rates are not highly variable, there are short-run changes in the ex ante real interest rate. We find that news about the one-month-ahead real interest rate is an important component of the innovation variance of the 1-month bill rate. There is a strong negative covariance between one-month-ahead forecasts of inflation and real interest rates, so that the short-term nominal interest rate would be considerably more variable if the ex ante real interest rate were constant.[15] Since the real interest rate does help to move the short-term interest rate, but has little impact on the long-term bond yield, we find that real interest rate news is also a major factor accounting for the variability of the yield spread between 10-year bonds and 1-month bills. These results are consistent with the findings of Fama (1990b).

We also find evidence that excess bond returns can be forecast using the same variables that help to forecast excess stock returns. This is consistent with the results of Fama and French (1989). However news about future excess returns contributes less to volatility in the bond market than in the stock market. The reason for this is that forecasts of excess bond returns place less weight on the slow-moving dividend-price ratio and therefore are less persistent than forecasts of excess stock returns.

During the 1980s, news about excess bond returns is negatively correlated with news about future inflation over the life of a 10-year bond. This reduces

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[14] Of course, real bond-pricing models can sometimes be reinterpreted as nominal bond-pricing models by changing to a nominal numeraire. However, this may affect the plausibility of the underlying equilibrium specification.

[15] This makes it unlikely that the inflation risk premium is zero, since inflation surprises are correlated with short-term changes in the investment opportunity set.

bond price variability because capital losses from higher expected inflation are partially offset by capital gains from lower expected excess bond returns. The correlation between excess bond returns and inflation has a different effect on the yield spread, however. News that inflation is higher tends to increase short-term expected inflation and the short-term nominal interest rate more than long-term expected inflation and the long-term nominal interest rate; thus positive inflation news tends to be associated with a decline in the yield spread. The negative correlation between term premiums and inflation accentuates this decline, so the variability of the yield spread is increased. Long-term bond yields "underreact" to inflation and yield spreads "overreact," as described by Campbell and Shiller (1984, 1991).

Finally, our results help to explain the correlation of stock and bond returns in postwar monthly U.S. data. There are several reasons why the correlation between these returns is so low. First, the only component which is common to both assets is the news about real interest rates, but this component has relatively little variability. Second, there is a strong positive correlation between news about future excess returns on bonds and stocks, as found by Fama and French (1989); but this is not sufficient to produce a large positive covariance between the two asset returns because news about future excess bond returns is not the major component of bond returns. Third, increases in long-run expected inflation tend to drive the stock market up and the bond market down. This makes bond and stock returns covary negatively, offsetting the positive covariance coming from the real interest rate and expected excess return effects.

Barsky (1989) has suggested that the weak correlation of bond and stock returns could be due to a tendency for equity risk premiums to increase when the short-term real interest rate falls. If term premiums are close to constant, declining real interest rates would be associated with a rising bond market but a flat or even declining stock market. Our empirical results do not support this explanation. We do not find that real interest rate changes are important in moving either bond or stock prices. Also, in the later part of our sample period we find a significantly *positive* correlation between news about real interest rates and news about equity premiums; in the earlier part of the period the correlation is negative but does not have an important influence on the covariance of bond and stock returns.

The major caveat about all the results presented here is that they are dependent on a particular specification of the information set available to investors. The results do not seem to be very sensitive to the number of lags we include in our VAR system, but it is always possible that there are omitted forecasting variables that could change the decompositions of excess returns.

The variance decompositions reported here should have several interesting applications in cross-sectional asset pricing. First, the methods of this paper can be applied to international stock market data to try to account for the common variation in different national stock price indexes. Second, the methods of this paper can be used to study the cross-sectional behavior of

assets' betas with the aggregate stock market. Betas, like variances and covariances, can be broken into components due to news about cash flows and news about future discount rates (Campbell and Mei (1992)). Finally, the importance of changing expected excess stock returns suggests that the intertemporal asset-pricing literature, which allows for changes in the investment opportunity set, is empirically relevant for postwar U.S. data. Intertemporal asset-pricing theory can be used to restrict the structure of the VAR models used in this paper (Campbell (1993)).

Appendix A: Bond Return Calculations

Define the log nominal price of an n-period nominal bond at time t as $p_{n,t}$. Define the log nominal 1-period holding return on a bond with n periods to maturity at time t, held from t to $t + 1$, as

$$b_{n,t+1} \equiv p_{n-1,t+1} - p_{n,t}. \tag{A1}$$

Equation (A1) can be thought of as a difference equation in the log bond price. It can be solved forward to the maturity date of the bond, using the fact that at this date the bond price is unity so its log price is zero: $p_{0,t+n} = 0$. We obtain

$$\begin{aligned} p_{n,t} &= -[\, b_{n,t+1} + b_{n-1,t+2} + \cdots + b_{1,t+n}\,] \\ &= -\sum_{i=0}^{n-1} b_{n-i,t+1+i}. \end{aligned} \tag{A2}$$

Equation (A2) holds ex post, but it also holds ex ante. If one takes expectations of equation (A2) at date t, the left-hand side remains unchanged because the nominal bond price is in the information set at time t. The right-hand side becomes a sum of expected future returns, rather than realized returns:

$$p_{n,t} = -E_t \sum_{i=0}^{n-1} b_{n-i,t+1+i}. \tag{A3}$$

Equation (A3) can be substituted into (A1) to express the log nominal bond return as a function of news about future nominal bond returns:

$$b_{n,t+1} - E_t b_{n,t+1} = -(E_{t+1} - E_t) \sum_{i=1}^{n-1} b_{n-i,t+1+i}. \tag{A4}$$

This equation expresses the well-known fact that nominal bond returns are known over the life of the bond, so that unexpected positive nominal returns today are always offset by decreases in expected future nominal returns.

For our purposes, it will be more useful to work with excess bond returns. We define the log excess 1-period bond return as

$$x_{n,t+1} \equiv b_{n,t+1} - \pi_{t+1} - r_{t+1}. \tag{A5}$$

To obtain (3) we substitute (A5) into (A4). To obtain (7) we substitute (A5) into (A3) and then use the fact that $y_{n,t} = -p_{n,t}/n$. Equation (8) follows straightforwardly.

Appendix B: VAR Calculations

Given the state vector and VAR system defined in Section I.*E*, the components of asset returns can be derived as follows. For stock returns, we have

$$\tilde{e}_{e,t+1} = e1' \sum_{j=1}^{\infty} \rho^j A^j w_{t+1} = e1' \rho A (I - \rho A)^{-1} w_{t+1}$$

$$\tilde{e}_{r,t+1} = e2' \sum_{j=0}^{\infty} \rho^j A^j w_{t+1} = e2' (I - \rho A)^{-1} w_{t+1}$$

$$\tilde{e}_{d,t+1} = \tilde{e}_{t+1} + \tilde{e}_{e,t+1} + \tilde{e}_{r,t+1}. \tag{B1}$$

The components of the excess bond return can be obtained in a similar manner. We have

$$\tilde{x}_{r,t+1} = e2' \sum_{j=1}^{n-1} A^j w_{t+1} = e2' (I - A)^{-1} (A - A^n) w_{t+1}$$

$$\tilde{x}_{\pi,t+1} = -\tilde{x}_{r,t+1} + e3' \left\{ (I - A)^{-1} \left[(n - 1)I + (I - A)^{-1} (A^n - A) \right] \right\} w_{t+1}$$

$$\tilde{x}_{x,t+1} = -\tilde{x}_{t+1} - \tilde{x}_{r,t+1} - \tilde{x}_{\pi,t+1}. \tag{B2}$$

For the short-term nominal interest rate decomposition, we have

$$\tilde{y}_{r,t+1} = -e2' A w_{t+1}$$

$$\tilde{y}_{\pi,t+1} = \tilde{x}_{2,t+1} - \tilde{y}_{r,t+1}. \tag{B3}$$

For the yield spread decomposition, we define a matrix $C_n = (1/n)(I - A)^{-1}(I - A^n) - I$. Then

$$\tilde{s}_{r,t+1} = -e2' A C_{n-1} w_{t+1}$$

$$\tilde{s}_{\pi,t+1} = -\tilde{s}_{r,t+1} + e3' (I - A)^{-1} A C_{n-1} w_{t+1}$$

$$\tilde{s}_{x,t+1} = \tilde{s}_{t+1} - \tilde{s}_{r,t+1} - \tilde{s}_{\pi,t+1}. \tag{B4}$$

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