Understanding Risk and Return

Understanding Risk and Return

John Y. Campbell

Harvard University

This paper uses an equilibrium multifactor model to interpret the cross-sectional pattern of postwar U.S. stock and bond returns. Priced factors include the return on a stock index, revisions in forecasts of future stock returns (to capture intertemporal hedging effects), and revisions in forecasts of future labor income growth (proxies for the return on human capital). Aggregate stock market risk is the main factor determining excess returns; but in the presence of human capital or stock market mean reversion, the coefficient of relative risk aversion is much higher than the price of stock market risk.

I. Introduction

How should the risk of an asset be measured? And what economic forces determine the price of risk, the additional return an investor gets for bearing additional risk? These two questions are among the most fundamental in finance. In this paper I argue that existing models do not address them adequately, and I propose a new way to get quantitative answers.

The oldest complete model of asset pricing, the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), measures the risk of an asset by the covariance of the asset's return with the return on all invested wealth, also known as the "market return." In empirical studies, the market return is commonly proxied by the return on

I am grateful to the National Science Foundation for financial support and to Sangjoon Kim and Chunsheng Zhou for able research assistance. Fischer Black, Gene Fama, Ravi Jagannathan, Greg Mankiw, Robert Shiller, and Robert Stambaugh; two anonymous referees; and seminar participants at Chicago Business School, Princeton, the Wharton School, and Yale made helpful comments on earlier versions of this paper.

[*Journal of Political Economy*, 1996, vol. 104, no. 2]

a diversified portfolio of common stocks. The price of market risk is determined by the risk aversion of investors; in an equilibrium version of the model estimated by Friend and Blume (1975), the price of risk is just the coefficient of relative risk aversion of a representative investor.

Although the CAPM is widely used by practitioners, it has come under attack from several directions. The assumptions used to derive the model have been criticized by Merton (1973) and others who have pointed out that in general an asset's risk should be measured by its covariance with the marginal utility of investors. In an intertemporal setting, this need not be the same as covariance with the market return, because innovations in marginal utility can be driven by changing expectations of future returns, which determine the marginal productivity of wealth, as well as by increments to wealth itself.

The main auxiliary assumption used to test the model—the assumption that the market return can be adequately proxied by a stock index return—has been challenged by Roll (1977). He argues that the market return cannot be measured accurately enough to test the CAPM.

In response to these critiques, many economists have estimated multifactor models in which risk is measured by covariances with several common factors. The factors must affect many assets, but otherwise they are not restricted by theory. In empirical work they have been specified in several different ways, through factor analysis of the covariance matrix of returns (Roll and Ross 1980), as returns on well-diversified portfolios of assets, or as innovations to important macroeconomic variables (Chen, Roll, and Ross 1986). Models of this sort require only very weak theoretical assumptions, and they appear to give a good empirical fit to the cross section of asset returns.

But multifactor models do not give clear answers to the two questions posed at the beginning of this paper. The models give little guidance in picking factors, and they are silent about the forces that determine factor risk prices. As Fama (1991, p. 1594) puts it, multifactor models "leave one hungry for economic insights about how the factors relate to uncertainties about consumption and portfolio opportunities that are of concern to investors, that is, the hedging arguments for multifactor models of Fama (1970) and Merton (1973)." In addition, "since multifactor models offer at best vague predictions about the variables that are important in returns and expected returns, there is the danger that measured relations between returns and economic factors are spurious, the result of special features of a particular sample (factor dredging)" (p. 1595).

This paper responds to the Merton and Roll critiques in a more structured fashion. I develop a simple discrete-time asset pricing model that allows for both changing investment opportunities and an important component of wealth—human capital—whose return may not be well proxied by the return on a stock index. Following Campbell (1993), I use log-linear approximations where they are necessary to make the model tractable and empirically implementable.

The resulting model has a standard multifactor form, but the identity and risk prices of the factors are determined by the time-series properties of the data and the risk aversion of a representative investor. Factors include the innovation in the return on a stock index (the traditional CAPM factor), innovations in variables that help to forecast future returns (hedging factors of the type discussed by Merton), and innovations in variables that help to forecast future labor income (proxies for the unobserved return on human capital). Other variables may affect many asset returns, but if they do not forecast returns or labor income, they will have zero risk prices and can be omitted from the model. The risk prices on the included factors are not free parameters, but are determined by the factors' importance in forecasting future returns or labor income.

It follows that empirical researchers should find priced factors not by running a factor analysis on the covariance matrix of returns, nor by selecting important macroeconomic variables. Instead, they should look at the time-series behavior of stock returns and labor income. The model links the vast time-series literature on asset returns to the equally vast cross-section literature, responding to Fama's call for "a coherent story that relates the variation through time in expected returns to models for the cross-section of expected returns" (1991, p. 1610).[1] This connection is intellectually satisfying, and it offers the practical benefit that researchers are less likely to detect spurious patterns when they must link time-series and cross-section findings.

The model of this paper is an alternative to the consumption-based capital asset pricing model, or CCAPM, derived by Breeden (1979) and Grossman and Shiller (1981). The CCAPM handles the Merton and Roll critiques of the CAPM by using the covariance with aggregate consumption instead of the covariance with the market as a measure of risk. The price of consumption risk is derived from the risk aversion of a representative investor. Although the CCAPM has

[1] Both the cross-sectional and time-series literatures are far too large to cite adequately. A partial list of cross-sectional references might include Roll and Ross (1980), Chan, Chen, and Hsieh (1985), Chen et al. (1986), Shanken and Weinstein (1990), Fama and French (1992, 1993), and Jagannathan and Wang (1994). A partial list of time-series references might include Fama and Schwert (1977*a*), Keim and Stambaugh (1986), Campbell (1987*b*), Campbell and Shiller (1988), Fama and French (1988*a*, 1988*b*, 1989), and Poterba and Summers (1988). Ferson and Harvey (1991) is one of the few papers that bridges these two literatures.

yielded many insights, it has at least two weaknesses. First, it does not measure an asset's risk in the way that investors presumably do, using covariances with variables that are exogenous to investors. Since investors choose consumption, consumption is endogenous from their perspective and the CCAPM cannot give a good account of the way they perceive risk. Second, the empirical performance of the CCAPM is poor: it is outperformed by the static CAPM (Mankiw and Shapiro 1986) and by unrestricted multifactor models. This may be due to measurement errors in consumption or discrepancies between aggregate consumption and the consumption of asset market participants. These problems do not mean that researchers should altogether abandon the use of consumption data, but it seems worthwhile to explore alternative approaches.

Accordingly, I follow Campbell (1993) and use a log-linear approximation to the budget constraint to get a closed-form solution for the consumption of a representative investor facing conditionally lognormal and homoskedastic asset returns, and maximizing the objective function proposed by Epstein and Zin (1989, 1991) and Weil (1989) (a generalization of power utility). From this it is easy to derive an asset pricing formula that makes no reference to consumption, instead relating assets' returns to their covariances with the market return and news about future market returns. The formula is in the spirit of Merton (1973) but is much easier to implement empirically. It generalizes straightforwardly to the case in which asset returns are conditionally heteroskedastic, provided that the elasticity of intertemporal substitution is sufficiently close to one.

In response to the Roll (1977) critique, I extend the Campbell (1993) model to allow for human capital as a component of wealth. I impute the return on human capital from data on aggregate labor income and asset returns. Finally, I develop an econometric framework in which the model can be confronted with historical data.

Several recent papers explore issues related to those considered here. Li (1991) and Hardouvelis, Kim, and Wizman (1992) estimate the Campbell (1993) intertemporal asset pricing model, assuming that the return on a stock index is an adequate proxy for the market portfolio return. Cochrane (1992) and Jagannathan and Wang (1994) show that a single-factor conditional asset pricing model, such as a conditional version of the CAPM, generally implies a multifactor unconditional asset pricing model. However, in their papers the additional factors are not related to intertemporal hedging by investors, and the risk prices on the factors are not restricted. Finally, a number of authors have allowed some role for human capital in asset pricing. Fama and Schwert (1977*b*) and Jagannathan and Wang (1994) use labor income growth to test Mayers's (1972) version of the CAPM allowing for human capital. Both these papers assume that labor income growth is unforecastable. Shiller's (1993) paper is closer to the present paper in that it uses a time-series model to construct innovations in the present value of aggregate income forecasts.

The paper is organized as follows. Section II reviews the theory in Campbell (1993), and Section III presents a strategy for measuring the return on the market portfolio. Section IV discusses econometric methodology. Section V describes the data, defines a set of state variables, and presents a preliminary time-series analysis. Section VI draws out implications for asset pricing, and Section VII briefly explores some implications for consumption. Section VIII offers conclusions.

II. Asset Pricing and the Determinants of Consumption

Approximating the Budget Constraint

The model considered by Campbell (1993) is a representative agent economy in which human capital is tradable along with other assets. Define W_t and C_t as aggregate wealth and consumption at the beginning of time t, and $R_{m,t+1}$ as the gross simple return on aggregate invested wealth ("the market"). The representative agent's dynamic budget constraint can then be written as

$$W_{t+1} = R_{m,t+1}(W_t - C_t). \tag{1}$$

Labor income does not appear explicitly in this budget constraint because the market value of tradable human capital is included in wealth.

The budget constraint in (1) is nonlinear because of the interaction between subtraction and multiplication. Consumption is first subtracted from wealth to get invested wealth, and invested wealth is then multiplied by the market return to get next period's wealth. Campbell suggests linearizing the budget constraint by dividing (1) by W_t, taking logs, and then using a first-order Taylor approximation around the mean log consumption/wealth ratio $c - w$. If one defines a parameter $\rho \equiv 1 - \exp(c - w)$, the approximation can be written as

$$\Delta w_{t+1} \approx r_{m,t+1} + k_w + \left(1 - \frac{1}{\rho}\right)(c_t - w_t), \tag{2}$$

where lowercase letters are used for logs and k_w is a constant that need not concern us here. Campbell shows that if the log consumption/wealth ratio is stationary, this approximation implies

$$c_{t+1} - E_t c_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{m,t+1+j} \\ - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \Delta c_{t+1+j}. \tag{3}$$

Equation (3) says that an upward surprise in consumption today must correspond to an unexpected return on wealth today (the first term in the first sum on the right-hand side of the equation), to news that future returns will be higher (the remaining terms in the first sum), or to a downward revision in expected future consumption growth (the second sum on the right-hand side). Intuitively, high consumption can be sustained only by high wealth or high returns on wealth; in their absence, high consumption today means lower consumption tomorrow.

The Consumer's Objective Function

The next step is to use a log-linear Euler equation to eliminate expected future consumption growth from the right-hand side of (3), leaving only current and expected future asset returns. Campbell (1993) uses the objective function proposed by Epstein and Zin (1989, 1991) and Weil (1989) in order to distinguish the coefficient of relative risk aversion and the elasticity of intertemporal substitution. In the standard model of time-separable power utility, relative risk aversion is the reciprocal of the elasticity of intertemporal substitution, but these concepts play quite different roles in the asset pricing theory. The Epstein-Zin-Weil objective function also allows intertemporal considerations to affect asset prices even when the consumption/wealth ratio is constant, something that is not possible with time-separable power utility.

The Epstein-Zin-Weil objective function is defined recursively by

$$U_t = \{(1-\beta)C_t^{1-(1/\sigma)} + \beta(E_t U_{t+1}^{1-\gamma})^{[1-(1/\sigma)]/(1-\gamma)}\}^{1/[1-(1/\sigma)]} \\ = [(1-\beta)C_t^{(1-\gamma)/\theta} + \beta(E_t U_{t+1}^{1-\gamma})^{1/\theta}]^{\theta/(1-\gamma)}. \tag{4}$$

Here γ is the coefficient of relative risk aversion, σ is the elasticity of intertemporal substitution, and θ is defined, following Giovannini and Weil (1989), as $\theta = (1-\gamma)/[1-(1/\sigma)]$. Note that in general the coefficient θ can have either sign. Important special cases of the model include the case in which the coefficient of relative risk aversion $\gamma \rightarrow 1$, so that $\theta \rightarrow 0$; the case in which the elasticity of intertemporal substitution $\sigma \rightarrow 1$, so that $\theta \rightarrow \infty$; and the case in which $\gamma = 1/\sigma$, so that $\theta = 1$. Inspection of (4) shows that this last case gives the standard time-separable power utility function with relative risk aversion γ. When both γ and σ equal one, the objective function is the time-separable log utility function.

Epstein and Zin (1989, 1991) have solved for the Euler equations corresponding to this objective function when the budget constraint is described by (1). Assume for the present that asset prices and consumption are conditionally homoskedastic. Also, either assume that asset prices and consumption are jointly lognormal or use a second-order Taylor approximation to the Euler equations. Then these equations can be written in log-linear form as

$$E_t \Delta c_{t+1} = \mu_m + \sigma E_t r_{m,t+1} \tag{5}$$

and

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_{ii}}{2} = \theta \frac{V_{ic}}{\sigma} + (1 - \theta) V_{im}. \tag{6}$$

In (5), μ_m is an intercept term related to the second moments of consumption and the market return, which have been assumed constant. In (6), $r_{f,t+1}$ is a riskless real interest rate, V_{ii} denotes $\mathrm{var}(r_{i,t+1} - E_t r_{i,t+1})$, V_{ic} denotes $\mathrm{cov}(r_{i,t+1} - E_t r_{i,t+1}, c_{t+1} - E_t c_{t+1})$, and V_{im} denotes $\mathrm{cov}(r_{i,t+1} - E_t r_{i,t+1}, r_{m,t+1} - E_t r_{m,t+1})$. The assumption of homoskedasticity ensures that the unconditional variances and covariances of innovations are the same as the constant conditional variances and covariances of these innovations.

Equation (5) is the familiar time-series Euler equation that one obtains also with power utility. It says that expected consumption growth is a constant plus the elasticity of intertemporal substitution times the expected return on the market portfolio.

Equation (6) is the implication of the model emphasized by Giovannini and Weil (1989). In this expression, all risk premia are constant over time because of the assumption that asset returns and consumption are homoskedastic. Equation (6) says that the expected excess log return on an asset, adjusted for one-half its own variance (a Jensen's inequality effect), is a weighted average of two covariances: the first covariance with consumption divided by the intertemporal elasticity of substitution (this gets a weight of θ) and the second covariance with the return on the market portfolio (this gets a weight of $1 - \theta$).

Three special cases are worth noting. When the objective function is a time-separable power utility function, the coefficient $\theta = 1$ and the model collapses to the log-linear CCAPM of Hansen and Singleton (1983). When the coefficient of relative risk aversion $\gamma = 1$, $\theta = 0$ and a logarithmic version of the static CAPM pricing formula holds. Most important for the present paper, as the elasticity of intertemporal substitution $\sigma \rightarrow 1$, the coefficient $\theta \rightarrow \infty$. At the same time the variability of the consumption/wealth ratio decreases so that the covariance $V_{ic} \rightarrow V_{im}$. It does not follow, however, that the risk premium is determined only by V_{im} in this case. Giovannini and Weil (1989) show that the convergence rates are such that asset pricing is not myopic when $\sigma = 1$ unless also $\gamma = 1$ (the log utility case).

Substituting out Consumption

These log-linear Euler equations can now be combined with the approximate log-linear budget constraint. Substituting (5) into (3), one obtains

$$c_{t+1} - E_t c_{t+1} = r_{m,t+1} - E_t r_{m,t+1} + (1 - \sigma)(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j}. \tag{7}$$

The intuition here is that an unexpected return on invested wealth has a one-for-one effect on consumption, no matter what the parameters of the utility function. (This follows from the scale independence of the objective function [4].) An increase in expected future returns has offsetting income and substitution effects on current consumption; it raises consumption if σ, the elasticity of intertemporal substitution, is less than one but lowers it if σ is greater than one.

Equation (7) implies that the covariance of any asset return with consumption can be rewritten in terms of covariances with the return on the market and revisions in expectations of future returns on the market. The covariance satisfies

$$\text{cov}(r_{i,t+1} - E_t r_{i,t+1}, c_{t+1} - E_t c_{t+1}) \equiv V_{ic} = V_{im} + (1 - \sigma) V_{ih}, \tag{8}$$

where $V_{ih} \equiv \text{cov}[r_{i,t+1} - E_t r_{i,t+1}, (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j}]$, the covariance of the unexpected return on asset i with good news about future returns on the market, that is, upward revisions in expected future returns. The use of the letter h here is intended to recall Merton's (1973) use of the word "hedging" to describe intertemporal components of asset demand.

Substituting (8) into (6) and using the definition of θ in terms of the underlying parameters σ and γ, one obtains a cross-sectional asset pricing formula that makes no reference to consumption:

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_{ii}}{2} = \gamma V_{im} + (\gamma - 1) V_{ih}. \tag{9}$$

Equation (9) is the starting point for the empirical work of this paper. It says that assets can be priced without direct reference to their covariance with consumption, using instead their covariances with the return on invested wealth and with news about future returns on invested wealth in the manner of Merton (1973). Moreover, the only parameter of the utility function that enters (9) is the coefficient of relative risk aversion γ. The elasticity of intertemporal substitution σ does not appear once consumption has been substituted out of the model.

Equation (9) expresses the risk premium (adjusted for the Jensen's inequality effect) as a weighted sum of two terms. The first term, with a weight of γ, is the asset's covariance with the market portfolio. The second term, with a weight of $\gamma - 1$, is the asset's covariance with news about future returns on the market. When $\gamma < 1$, assets that do well when there is good news about future returns on the market have lower mean returns; but when $\gamma > 1$, such assets have higher mean returns. The intuitive explanation is that such assets are desirable because they enable the consumer to profit from improved investment opportunities, but undesirable because they reduce the consumer's ability to hedge against a deterioration in investment opportunities. When $\gamma < 1$, the former effect dominates and consumers are willing to accept a lower return in order to hold assets that pay off when wealth is most productive. When $\gamma > 1$, the latter effect dominates and consumers require a higher return to hold such assets.

Equation (9) implies that a logarithmic version of the static CAPM holds if $\gamma = 1$, if $V_{ih} = 0$ for all assets, or (less restrictively) if V_{ih} is proportional to V_{im} for all assets. That is, risk aversion must take exactly the right value for investors to ignore intertemporal considerations, asset returns must lack the intertemporal risks that give rise to hedging demands, or assets' intertemporal risks must be perfectly cross-sectionally correlated with market risk. In the first case, the price of market risk is $\gamma = 1$; in the second case, the price of market risk is γ, which can take any value; and in the third case, the price of market risk is not necessarily equal to γ. Instead, if $V_{ih} = \kappa V_{im}$ for some coefficient κ, then the price of market risk is $\gamma + (\gamma - 1)\kappa$.

In anticipation of the empirical results to be reported below, postwar U.S. data on bonds and size and industry portfolios of common stocks suggest that the first two cases do not hold even approximately, but the third case describes these assets surprisingly well. Most of the cross-sectional variation in returns explained by the model is explained by cross-sectional variation in V_{im}, but the price of market risk is much smaller than the coefficient of relative risk aversion γ because V_{im} and V_{ih} are strongly negatively correlated across assets.

Heteroskedasticity

So far I have assumed that asset returns and consumption (or, equivalently, asset returns and news about future asset returns) are jointly homoskedastic. This assumption simplifies the analysis but is unrealistic. Campbell (1993) discusses various ways to allow for heteroskedasticity. The simplest approach is to assume that the elasticity of intertemporal substitution $\sigma = 1$, in which case the asset pricing formula (9) holds exactly when asset returns are homoskedastic. With heteroskedastic returns, the formula still holds exactly if one uses conditional expected excess returns and conditional variances and covariances: V_{ii} becomes $V_{ii,t}$ and so forth. One can then take unconditional expectations of the conditional version of (9) to put it back in unconditional form. (This is valid because all variances and covariances pertain to innovations with respect to a conditional information set.) In this paper I assume that $\sigma = 1$ or is close enough that (9) is a good approximate asset pricing model even in the presence of heteroskedasticity, and I test the unconditional implications of this model.[2]

III. Human Capital and the Market Return

The asset pricing model developed in Section II is empirically testable only if one can measure the return on the market portfolio. Financial economists commonly proxy the market portfolio by a value-weighted index of common stocks, but this practice is questionable. Even if the stock index return captures the return on financial wealth, as argued by Stambaugh (1982), it may not capture the return on human wealth. Approximately two-thirds of gross national product goes to labor and only one-third to capital, so human wealth is likely to be about two-thirds of total wealth and twice financial wealth. This suggests that the omission of human wealth may be a serious matter.

Here I propose a simple way to bring human wealth into the analysis. I start with the relationship

$$R_{m,t+1} = (1 - v_t)R_{a,t+1} + v_t R_{y,t+1}, \qquad (10)$$

where v_t is the ratio of human wealth to total wealth, $R_{a,t+1}$ is the gross simple return on financial wealth (a refers to financial assets), and $R_{y,t+1}$ is the gross simple return on human wealth (y refers to the stream of labor income).

[2] Nieuwland (1991) and Restoy (1992) discuss other ways to extend the framework of Campbell (1993) to handle heteroskedasticity.

Equation (10) relates simple returns and has time-varying coefficients. To get a tractable intertemporal model, one needs an equation for log returns with constant coefficients. This can be obtained by taking logs of (10) and linearizing around the means of ν_t, $r_{a,t+1}$, and $r_{y,t+1}$, assuming that the means of the latter two variables are the same, that is, that the average log return on financial wealth equals the average log return on human wealth. The result is

$$r_{m,t+1} \approx k_m + (1-\nu) r_{a,t+1} + \nu r_{y,t+1}, \tag{11}$$

where k_m is a constant that plays no role in what follows, and ν is the mean of ν_t. This approximation can also be obtained by noting that $r_{a,t+1} \approx R_{a,t+1} - 1$ and $r_{y,t+1} \approx R_{y,t+1} - 1$, and linearizing around the mean of ν_t.

Of course, the return on human wealth is not directly observable. What is observable is aggregate labor income y_t, which can be thought of as the dividend on human wealth.[3] If I assume that the conditional expected return on financial wealth equals the conditional expected return on human wealth (a slightly stronger assumption than the one used to derive [11]), then the log-linear approximation of Campbell and Shiller (1988) and Campbell (1991) implies that

$$\begin{aligned} r_{y,t+1} - E_t r_{y,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta y_{t+1+j} \\ - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{a,t+1+j}. \end{aligned} \tag{12}$$

Increases in expected future labor income cause a positive return on human capital, but increases in expected future asset returns cause a negative return on human capital because the labor income stream is now discounted at a higher rate and is therefore worth less today. Equation (12) is similar to the formula used in Shiller (1993), except that Shiller discounts aggregate income at a constant rate. In other words, he assumes $(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{a,t+1+j} = 0$ and works only with the first summation in (12). Fama and Schwert (1977*b*) and Jagannathan and Wang (1994) also discount income at a constant rate, but in addition they assume that labor income growth is unforecastable so that $(E_{t+1} - E_t)\Delta y_{t+1+j} = 0$ for $j > 0$. They work only with the first term in the first summation in (12): $r_{y,t+1} - E_t r_{y,t+1} = \Delta y_{t+1} - E_t \Delta y_{t+1} = \Delta y_{t+1} - E\Delta y_{t+1}$.

[3] This statement abstracts from variations in work effort that might affect marginal utility in a fully specified model with endogenous labor supply.

Substituting (12) into (11) gives

$$
\begin{aligned}
r_{m,t+1} - E_t r_{m,t+1} = (1-\nu)(r_{a,t+1} - E_t r_{a,t+1}) \\
+ \nu(E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta y_{t+1+j} \\
- \nu(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{a,t+1+j}.
\end{aligned} \tag{13}
$$

Because I am now using forecasts of future labor income to calculate the human capital component of the market return, forecasts of future stock returns appear in the formula as the discount rates applied to labor income.

Substituting (13) into (7), I obtain

$$
\begin{aligned}
c_{t+1} - E_t c_{t+1} = (1-\nu)(r_{a,t+1} - E_t r_{a,t+1}) \\
+ \nu(E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta y_{t+1+j} \\
+ (1-\sigma-\nu)(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{a,t+1+j}.
\end{aligned} \tag{14}
$$

Changes in interest rates (expected future stock returns) affect consumption directly through their effect on the value of human wealth, as well as indirectly through intertemporal substitution. The former effect depends only on ν, whereas the latter depends on σ. When $\nu = 0$, (14) gives the conventional result that increases in interest rates drive down consumption only if $\sigma > 1$. As human capital becomes more important, however, interest rate increases drive down consumption even with lower values of σ. In the extreme case in which $\nu = 1$, so that there is only human wealth and no financial wealth, interest rate increases drive down consumption for any value of σ. The existence of human capital therefore helps to reconcile evidence that the elasticity of intertemporal substitution is low (Hall 1988; Campbell and Mankiw 1989) with the widespread belief among macroeconomists that consumption falls when interest rates rise.[4]

This paper focuses on the risk premium formula (9), which becomes

$$
E_t r_{i,t+1} - r_{f,t+1} + \frac{V_{ii}}{2} = \gamma(1-\nu)V_{ia} + \gamma\nu V_{iy} + [\gamma(1-\nu) - 1]V_{ih}, \tag{15}
$$

[4] Summers (1982) has also emphasized the importance of human capital in determining the response of consumption to interest rates.

where $V_{iy} \equiv \text{cov}[r_{i,t+1} - E_t r_{i,t+1}, (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta y_{t+1+j}]$, the covariance of the return on asset i with good news about current and future labor income. This need not be the same, of course, as the covariance of the return on asset i with labor income growth over one period. The term V_{iy} appears in (15) with a weight of $\gamma\nu$, whereas the covariance with the stock market return V_{ia} has a weight of $\gamma(1 - \nu)$. Since ν is likely to be on the order of two-thirds, this formula shows that labor income risk can be important in pricing assets.

Once human capital is in the model, the asset pricing formula does not collapse to the standard empirical version of the CAPM even when asset pricing is myopic. When $\gamma = 1$, for example, (15) says that $E_t r_{i,t+1} - r_{f,t+1} + (V_{ii}/2) = (1 - \nu)V_{ia} + \nu(V_{iy} - V_{ih})$. Here an asset's mean return equals its covariance with the market return, but the covariance with the market return is a weighted average, with weights $1 - \nu$ and ν, of the covariance with the financial and human capital components of the market. The covariance with the human capital component is measured by $V_{iy} - V_{ih}$ since changing discount rates can affect the value of human capital. This expression is equivalent to the standard empirical CAPM formula only if there is no human capital so that $\nu = 0$.

IV. Econometric Methodology

A Vector Autoregressive Factor Model

To derive testable implications of the asset pricing formula (15), I adapt the vector autoregressive (VAR) approach of Campbell (1991). I write the real stock index return as the first element of a K-element state vector $\mathbf{z}_t$ and real labor income growth as the second element. The other elements of $\mathbf{z}_t$ are variables that are known to the market by the end of period t and are relevant for forecasting future stock returns and labor income growth. For simplicity, I assume that all the variables in $\mathbf{z}_t$ have zero means or have been demeaned before the analysis begins, and I assume that the vector $\mathbf{z}_t$ follows a first-order VAR:

$$\mathbf{z}_{t+1} = \mathbf{A}\mathbf{z}_t + \boldsymbol{\epsilon}_{t+1}. \tag{16}$$

The assumption that the VAR is first-order is not restrictive since a higher-order VAR can always be stacked into first-order (companion) form in the manner discussed by Campbell and Shiller (1988). The matrix **A** is known as the companion matrix of the VAR.[5] The advan-

[5] As is well known, VAR systems can be normalized in different ways. For example, the variables in the state vector can be orthogonalized so that the variance-covariance matrix of the error vector $\boldsymbol{\epsilon}$ is diagonal. The results given below hold for any observationally equivalent normalization of the VAR system.

tage of working with a first-order VAR is that it generates simple multiperiod forecasts of future returns:

$$E_t\mathbf{z}_{t+1+j} = \mathbf{A}^{j+1}\mathbf{z}_t. \tag{17}$$

Next I define a K-element vector $\mathbf{e1}$, whose first element is one and whose other elements are all zero. This vector picks out the stock return r_{at} from the vector $\mathbf{z}_t$: $r_{at} = \mathbf{e1}'\mathbf{z}_t$, and $r_{a,t+1} - E_t r_{a,t+1} = \mathbf{e1}'\boldsymbol{\epsilon}_{t+1}$. Similarly, I define a K-element vector $\mathbf{e2}$, whose second element is one and whose other elements are all zero, which picks out labor income growth Δy_t from the vector $\mathbf{z}_t$.

The discounted sum of forecast revisions in stock returns can now be written as

$$\begin{aligned}(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{a,t+1+j} &= \mathbf{e1}'\sum_{j=1}^{\infty} \rho^j \mathbf{A}^j \boldsymbol{\epsilon}_{t+1} \\ &= \mathbf{e1}'\rho\mathbf{A}(\mathbf{I} - \rho\mathbf{A})^{-1}\boldsymbol{\epsilon}_{t+1} \\ &= \boldsymbol{\lambda}_h'\boldsymbol{\epsilon}_{t+1},\end{aligned} \tag{18}$$

where $\boldsymbol{\lambda}_h'$ is defined to equal $\mathbf{e1}'\rho\mathbf{A}(\mathbf{I} - \rho\mathbf{A})^{-1}$, a nonlinear function of the VAR coefficients. The elements of the vector $\boldsymbol{\lambda}_h$ measure the importance of each state variable in forecasting future returns on the market. If a particular element $\lambda_{h,k}$ is large and positive, then a positive shock to variable k is an important piece of good news about future investment opportunities.

Similarly, the discounted sum of revisions in current and expected future labor income growth is

$$\begin{aligned}(E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta y_{t+1+j} &= \mathbf{e2}'\sum_{j=0}^{\infty} \rho^j \mathbf{A}^j \boldsymbol{\epsilon}_{t+1} \\ &= \mathbf{e2}'(\mathbf{I} - \rho\mathbf{A})^{-1}\boldsymbol{\epsilon}_{t+1} \\ &= \boldsymbol{\lambda}_y'\boldsymbol{\epsilon}_{t+1},\end{aligned} \tag{19}$$

where $\boldsymbol{\lambda}_y'$ is defined to equal $\mathbf{e2}'(\mathbf{I} - \rho\mathbf{A})^{-1}$. The form of $\boldsymbol{\lambda}_y$ differs slightly from the form of $\boldsymbol{\lambda}_h$ because the summation in (19) starts at $j = 0$ rather than at $j = 1$ as in (18). The elements of $\boldsymbol{\lambda}_y$ measure the importance of each state variable in forecasting current and future labor income.

I now define $V_{ik} \equiv \text{cov}_t(r_{i,t+1}, \epsilon_{k,t+1})$, where $\epsilon_{k,t+1}$ is the kth element of $\boldsymbol{\epsilon}_{t+1}$. Since the first element of the state vector is the stock index return, $V_{i1} = V_{ia}$. Then equation (15) implies that

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_{ii}}{2} = \gamma(1-\nu)V_{i1} + \sum_{k=1}^{K} \{\gamma\nu\lambda_{y,k} + [\gamma(1-\nu) - 1]\lambda_{h,k}\} V_{ik}. \tag{20}$$

This is a standard K-factor asset pricing model of the type implied by the arbitrage pricing theory of Ross (1976) and many other financial models. The term V_{ik} is the covariance of asset i with factor k, and (20) says that the expected log excess return on asset i, adjusted for the effect of Jensen's inequality, is linear in the covariances of the return with the K factors.

The contribution of the intertemporal optimization problem is a set of restrictions on the risk prices of the factors. Factors have large risk prices if they are good forecasters of labor income growth or expected future stock returns. The intertemporal model with human capital thus implies that priced factors should be found not by running a factor analysis on the covariance matrix of returns (Roll and Ross 1980) nor by selecting important macroeconomic variables (Chen et al. 1986). Instead, innovations in variables that have been shown to forecast stock returns and labor income should be used in cross-sectional asset pricing studies. This is the strategy adopted in the empirical work of this paper.

Estimating the Model

A natural approach for estimating and testing asset pricing models is the generalized method of moments (GMM) of Hansen (1982). To use GMM, one must define a set of orthogonality conditions that identify the parameters of the model. If there are more orthogonality conditions than parameters, then the model is overidentified and can be tested following Hansen (1982). Hall (1993) and Ogaki (1993) are useful recent surveys of GMM methodology. This section discusses the orthogonality conditions implied by the VAR factor asset pricing model. For simplicity, I first describe the case in which asset returns are conditionally homoskedastic.

It is useful to think of the orthogonality conditions in three blocks. First, there are the orthogonality conditions that identify the VAR system (16). We have

$$\mathbf{z}_{t+1} - \mathbf{A}\mathbf{z}_t \equiv \boldsymbol{\epsilon}_{t+1} \perp \mathbf{z}_t, \tag{21}$$

where the symbol $\perp$ indicates orthogonality. Since there are K variables in the state vector $\mathbf{z}_t$, there are K^2 parameters in the matrix

A and equation (21) defines K^2 orthogonality conditions. Taken in isolation, the VAR system is just-identified.[6]

Second, there are orthogonality conditions that identify the vector of mean excess returns on assets. If we are working with I excess returns $e_{i,t+1} = r_{i,t+1} - r_{f,t+1}$, $i = 1, \ldots, I$, then the vector of excess returns $\mathbf{e}_{t+1}$ and the vector of unconditional means $\boldsymbol{\mu}$ are both $I \times 1$. We have

$$\mathbf{e}_{t+1} - \boldsymbol{\mu} \equiv \boldsymbol{\eta}_{t+1} \perp \{1, \mathbf{z}_t\}, \tag{22}$$

which gives $I(K + 1)$ orthogonality conditions to identify I parameters. There are IK overidentifying restrictions in this part of the model arising from the restriction that expected excess returns are constant through time.

An unrestricted factor asset pricing model can be written as

$$\mu_i + \frac{V_{ii}}{2} = \sum_{k=1}^{K} p_k V_{ik}, \tag{23}$$

where p_k is the price of risk for the kth factor. To estimate this, we note that $V_{ii} = E[\eta_{i,t+1}^2]$ and $V_{ik} = E[\eta_{i,t+1}\epsilon_{k,t+1}]$. Thus we can define an ex post version of (23):

$$u_{i,t+1} \equiv \mu_i + {}^1\!/\!_2\,\eta_{i,t+1}^2 - \sum_{k=1}^{K} p_k \eta_{i,t+1}\epsilon_{k,t+1} \perp \{1, \mathbf{z}_t\}. \tag{24}$$

This gives $I(K + 1)$ orthogonality conditions to identify only K new parameters p_k. Hence there are $IK + I - K$ overidentifying restrictions arising from this part of the system.

When one adds up across the three parts of the model, the homoskedastic model with free factor risk prices has $K^2 + I + K$ parameters, $K^2 + 2I(K + 1)$ orthogonality conditions, and $2IK + I - K$ restrictions. The intertemporal model (20) says that the K factor risk prices p_k are functions of the VAR parameters and the coefficient of relative risk aversion γ; this reduces the number of parameters and increases the number of restrictions by $K - 1$, giving $K^2 + I + 1$ parameters and $2IK + I - 1$ restrictions.

As stated so far, the asset pricing model is very unlikely to describe the data because homoskedasticity requires that squared innovations in factors and returns are orthogonal to the instrument vector $\mathbf{z}_t$. If asset returns are heteroskedastic, but one uses the unconditional

[6] Recall that, for simplicity, the variables in the state vector are assumed to have been demeaned beforehand. Estimation of means can be incorporated into (21) without difficulty; the number of orthogonality conditions and the number of parameters to be estimated both increase by K. The VAR system remains just-identified.

moments of return innovations to estimate the model, then one can drop $\mathbf{z}_t$ from the instrument list in equations (22) and (24). The model with free factor risk prices has only $K^2 + I + K$ parameters, $K^2 + 2I$ orthogonality conditions, and $I - K$ overidentifying restrictions, whereas the intertemporal model has $K^2 + I + 1$ parameters and $I - 1$ overidentifying restrictions. This is the main approach used in the empirical work below.

Alternatively, one can apply the heteroskedastic asset pricing model to conditional moments of returns. The VAR block of the model remains unchanged, but the block of the model defining mean returns becomes

$$\mathbf{e}_{t+1} - \boldsymbol{\mu} - \mathbf{M}\mathbf{z}_t \equiv \boldsymbol{\eta}_{t+1} \perp \{1, \mathbf{z}_t\}, \tag{25}$$

which gives $I(K + 1)$ orthogonality conditions to identify $I(K + 1)$ parameters. There are no overidentifying restrictions in this part of the model because mean returns now vary with the instruments as described by the matrix of parameters $\mathbf{M}$. The factor asset pricing block of the model becomes

$$u_{i,t+1} \equiv \mu_i + \mathbf{M}_i\mathbf{z}_t + \tfrac{1}{2}\eta_{i,t+1}^2 - \sum_{k=1}^{K} p_k \eta_{i,t+1}\epsilon_{k,t+1} \perp \{1, \mathbf{z}_t\}. \tag{26}$$

This gives $I(K + 1)$ orthogonality conditions to identify only K new parameters p_k. As in the homoskedastic model, there are $IK + I - K$ overidentifying restrictions arising from this part of the system. When one adds up across the three parts of the conditional model, there are in total $(I + K)(K + 1)$ parameters, $K^2 + 2I(K + 1)$ orthogonality conditions, and $I(K + 1) - K$ restrictions in the model with free factor risk prices. The intertemporal model subtracts $K - 1$ parameters and adds $K - 1$ restrictions for a total of $I(K + 1) - 1$ restrictions.

V. Data and Time-Series Analysis

Data

This paper uses two separate data sets. The first data set is monthly and runs from January 1952 through December 1990, giving 468 observations.[7] The second data set, an update of that used in Campbell and Shiller (1988), is annual and runs from 1871 through 1990, giving 120 observations. All the tables report monthly results in panel A and annual results in panel B.

[7] Starting in 1952 avoids the period of interest rate pegging before the Fed-Treasury Accord of 1951. The dynamics of interest rates were quite different during that period.

The first step in implementing the VAR factor model is to define the variables that enter the state vector $\mathbf{z}_t$. These variables play a double role in the empirical work. First, they are *forecasting variables*, which should be chosen for their ability to predict market returns and labor income growth. Second, innovations in these variables are *factors* in a cross-sectional asset pricing model, so they should be chosen for their ability to explain the cross-sectional pattern of asset returns. If the intertemporal asset pricing model (20) is correct, then these two criteria for choosing state variables coincide.

Panel A of table 1 lists the state variables used in the monthly model. The analysis requires the first two variables to be a real stock index return RVW (the value-weighted index return from the Center for Research in Security Prices [CRSP] tape) and real labor income growth LBR (obtained from Citibase). Both series are deflated using the consumer price index (CPI), adjusted before 1983 to reflect the improved treatment of housing costs that is used in the official index only after 1983.

The remaining variables in the system are the dividend yield on the CRSP value-weighted index DIV (measured in standard fashion as a 1-year backward moving average of dividends divided by the most recent stock price); the "relative bill rate" RTB (the difference between the 1-month Treasury bill rate from the CRSP Fama file and its 1-year backward moving average); and the yield spread between long- and short-term government bonds TRM (obtained from the *Federal Reserve Bulletin*). All three of these variables have been found to forecast asset returns. The variable RTB, which has been used by Campbell (1991) and Hodrick (1992), can be thought of as a stochastically detrended short-term interest rate. It is equivalent to a triangular weighted average of changes in the short rate, so it is stationary even if there is a unit root in the short rate. Innovations in RTB are effectively innovations in the short rate, so by including RTB and TRM, I allow short- and long-term interest rate innovations to be priced factors in the cross-sectional model.

The variables used here include many of the forecasting variables used in the time-series work of Campbell (1987, 1991), Chen (1991), Ferson and Harvey (1991), Li (1991), and Hodrick (1992). Innovations in these variables are similar to factors used in the cross-sectional work of Chan et al. (1985), Chen et al. (1986), Shanken and Weinstein (1990), Ferson and Harvey (1991), and Li (1991). However, parsimony is particularly important in the VAR system because the number of parameters to be estimated increases with the square of the number of variables. For this reason, some variables used in previous work are omitted here. The default spread, for example, is omitted because it has no marginal explanatory power for stock returns or

TABLE 1

VARIABLE DEFINITIONS

Code	Variable	Source
	A. Monthly, 1952–90*	
RVW	Real value-weighted stock index return	CRSP
LBR	Real labor income growth rate	Citibase
DIV	Dividend yield on value-weighted index	CRSP
RTB	Relative bill rate (bill rate less 1-year moving average)	CRSP Fama file
TRM	Long-short government bond yield spread	*Federal Reserve Bulletin*
Size 1–10	Return on annually rebalanced size deciles (1 small, 10 large)	CRSP
PET	Petroleum industry return (SIC 13, 29)	CRSP
FRE	Finance/real estate industry return (SIC 60–69)	CRSP
CDR	Consumer durables industry return (SIC 25, 30, 36–37, 50, 55, 57)	CRSP
BAS	Basic industry return (SIC 10, 12, 14, 24, 26, 28, 33)	CRSP
FTB	Food/tobacco industry return (SIC 1, 20, 21, 54)	CRSP
CNS	Construction industry return (SIC 15–17, 32, 52)	CRSP
CAP	Capital goods industry return (SIC 34–35, 38)	CRSP
TRN	Transportation industry return (SIC 40–42, 44, 45, 47)	CRSP
UTI	Utilities industry return (SIC 46, 48, 49)	CRSP
TEX	Textiles/trade industry return (SIC 22–23, 31, 51, 53, 56, 59)	CRSP
SVS	Services industry return (SIC 72–73, 75, 80, 82, 89)	CRSP
LSR	Leisure industry return (SIC 27, 58, 70, 78–79)	CRSP
LTG	Long-term government bond return	Ibbotson Associates
STG	Short-term government bond return	Ibbotson Associates
CRP	Corporate bond return	Ibbotson Associates
	B. Annual, 1871–1990†	
RVW	Real return on Cowles/Standard & Poors (S&P) index	Campbell-Shiller (1988), updated from S&P
GNP	Real GNP growth rate	1871–1929: Romer (1989); 1930–90: National Income and Product Accounts
DIV	Dividend yield on Cowles/S&P index	Campbell-Shiller (1988), updated from S&P
TRM	Long-short government bond yield spread	Long rate: Siegel (1992); short rate: Campbell-Shiller (1988), updated from S&P
LTG	Long-term government bond return	Siegel (1992)
GLD	Return on gold	Siegel (1992)

* Real series are deflated using the CPI adjusted for housing costs before 1983 in the manner adopted for the official CPI after 1983. Stock portfolio returns are value-weighted. Stock and bond returns are measured as an excess over the 1-month Treasury bill rate unless otherwise stated.

† Real series are deflated using the GNP deflator.

income when the dividend yield is in the system (Fama and French 1989; Chen 1991). The return on a small stock portfolio is omitted because it is highly correlated with the value-weighted index return and does not forecast that return or labor income. The inflation rate and the industrial production growth rate are also omitted since the nominal short rate and labor income should be reasonable proxies for these variables.

The remainder of panel A of table 1 lists the portfolios used to measure the cross-sectional pattern of returns. Following Ferson and Harvey (1991), I use 10 value-weighted size portfolios that are rebalanced annually, 12 value-weighted industry portfolios grouped by two-digit Standard Industrial Classification (SIC) codes, and three bond portfolios.[8] This gives 25 portfolios with a fairly wide range of average returns.

Panel B of table 1 summarizes the state variables and portfolios used in the annual model. The state variables are as similar as possible to those in the monthly model, but there are two main changes. First, labor income data are not available over the period 1871–1990, so I use GNP data instead. There is some controversy about the measurement of GNP before 1929; I use Romer's (1989) series. Second, the relative bill rate cannot be calculated from annual interest rate data. Since the behavior of short-term nominal interest rates has changed several times during the last century and since parsimony is important given the smaller number of observations in the annual model, I drop the short-term nominal interest rate and work with four rather than five factors.

Far fewer portfolio returns are available over the period 1871–1990 than over the period 1952–90. Besides the return on the stock index itself, I use returns on long-term government bonds and on gold, taken from Siegel (1992).

Dynamics of the State Variables

Panel A of table 2 summarizes the dynamic behavior of the state variables. The table reports the coefficients in a one-lag VAR, estimated monthly in panel A and annually in panel B. The matrix of coefficients is the VAR companion matrix denoted by **A** in equation (16). All variables are measured in percentage points, at a monthly rate in panel A and at an annual rate in panel B. Table 2 also reports the R^2 statistic and the standard error of estimate for each equation in the VAR, and a matrix giving the variances, covariances, and corre-

[8] These portfolios were constructed from the raw CRSP data and then checked against the Ferson-Harvey data, kindly provided by Wayne Ferson.

TABLE 2

VAR SUMMARY: DYNAMICS OF RISK FACTORS

A. MONTHLY, 1952–90

DEPENDENT VARIABLE	REGRESSORS RVW	LBR	DIV	RTB	TRM	R^2
RVW	.029	.270	6.903	−6.284	4.099	.067
	(.058)	(.363)	(2.864)	(3.793)	(2.854)	(4.15)
LBR	−.008	.132	−1.441	1.012	.999	.101
	(.006)	(.066)	(.371)	(.326)	(.233)	(.519)
DIV	−.000	−.000	.979	.031	−.010	.957
	(.000)	(.001)	(.011)	(.014)	(.010)	(.015)
RTB	.001	.007	−.081	.806	.054	.595
	(.001)	(.005)	(.049)	(.065)	(.037)	(.056)
TRM	−.001	−.004	.069	.097	.926	.768
	(.001)	(.005)	(.047)	(.061)	(.038)	(.056)

Innovation Variances, Covariances, and Correlations*

SHOCKS TO	SHOCKS TO RVW	LBR	DIV	RTB	TRM
RVW	17.04	**.169**	**−.942**	**−.063**	**−.019**
LBR	.360	.266	**−.129**	**.048**	**−.051**
DIV	−.057	−.001	.000	**.078**	**.006**
RTB	−.015	.001	.000	.003	**−.938**
TRM	−.004	−.001	.000	−.003	.003

B. ANNUAL, 1871–1990

DEPENDENT VARIABLE	REGRESSORS RVW	GNP	DIV	TRM	R^2
RVW	.171	.189	2.938	−1.214	.065
	(.120)	(.331)	(1.067)	(1.139)	(16.8)
GNP	.064	.319	.129	.752	.236
	(.029)	(.111)	(.326)	(.346)	(4.5)
DIV	.003	.007	.686	.012	.443
	(.007)	(.029)	(.071)	(.070)	(1.1)
TRM	.002	−.030	.111	.609	.362
	(.007)	(.017)	(.075)	(.093)	(1.2)

Innovation Variances, Covariances, and Correlations*

SHOCKS TO	SHOCKS TO RVW	GNP	DIV	TRM
RVW	273.2	**.130**	**−.751**	**.263**
GNP	9.595	19.94	**−.052**	**.044**
DIV	−13.13	−.245	1.120	**−.259**
TRM	4.953	.223	−.312	1.295

NOTE.—Standard errors are in parentheses.
* Correlations are in boldface above the diagonal.

lations of innovations to the system. (Correlations are reported in boldface above the diagonal of the matrix.)

The first row of panel A of table 2 shows the monthly forecasting equation for the real value-weighted stock index RVW. This equation is similar to many that have been estimated in the literature, and the pattern of coefficients is quite familiar. There is minimal serial correlation in monthly stock returns; hence the coefficient on lagged RVW is small and statistically insignificant. Past labor income growth LBR also has little effect on stock returns. However, the dividend yield DIV has a significant positive coefficient, and the interest rate variables RTB and TRM enter with negative and positive signs, respectively. These variables are jointly although not individually significant. The equation has a modest R^2 of .07, and the standard deviation of stock return innovations is about 4 percent per month. The annual forecasting equation, reported in panel B, also has a strongly significant dividend yield coefficient, but the other variables play little role in forecasting stock returns. The R^2 is again about .07, and the standard deviation of stock return innovations is about 17 percent per year.

The second row of panel A of table 2 shows the monthly forecasting equation for real labor income growth LBR. Lagged labor income growth has a marginally significant positive coefficient, whereas the term spread and relative bill rate have strongly significant positive coefficients and the dividend yield has a significant negative coefficient. The R^2 is .10, and the standard deviation of monthly innovations to labor income is about 0.5 percent per month.[9] The annual model estimated in panel B has strong positive effects from lagged GNP growth and the term spread. The annual R^2 is .24, and the standard deviation of annual innovations to labor income is about 4.5 percent. These results strongly reject the assumption of Fama and Schwert (1977*b*) and Jagannathan and Wang (1994) that labor income growth is unforecastable.

The remaining rows of panel A of table 2 give the monthly dynamics of the forecasting variables. To a first approximation the variables DIV, RTB, and TRM all behave like persistent AR(1) processes with coefficients of 0.98, 0.81, and 0.93, respectively, although some other variables do enter. In particular, the relative bill rate helps to forecast

[9] Chen (1991) and Estrella and Hardouvelis (1991) estimate a simple quarterly postwar regression of GNP growth on the term spread and find a significant positive coefficient. Chen also runs simple quarterly regressions of GNP growth on other variables in the VAR system, finding significant negative coefficients on lagged RVW and DIV and a negative coefficient on RTB. Of course, one cannot directly compare these simple regression coefficients with the multiple regression coefficients estimated in this paper.

the dividend yield. The panel B results for annual data are comparable, but as one would expect, the own lag coefficients tend to be smaller with lower-frequency data.

Finally, table 2 reports the variances, covariances, and correlations of innovations to the VAR system. Innovations to income are much less volatile than stock returns, suggesting that market risk will be overstated by the traditional procedure, which uses stock returns alone. Innovations to the other state variables are much less volatile again. Also, there are large negative correlations between innovations to RVW and DIV and (in monthly data) between innovations to RTB and TRM.

These correlations and differences in volatility make it hard to interpret estimation results for a VAR factor model unless the factors are orthogonalized and scaled in some way. I proceed in the manner of Sims (1980), triangularizing the system so that the innovation in RVW is unaffected, the orthogonalized innovation in LBR is that component of the original LBR innovation orthogonal to RVW, the orthogonalized innovation in DIV is that component of the original DIV innovation orthogonal to RVW and LBR, and so on. I also scale all innovations to have the same variance as the innovation in RVW. The variables in the system are ordered so that the resulting factors are easy to interpret. The orthogonalized innovation to DIV is a change in the dividend/price ratio with no change in the stock return; hence it can be interpreted as a shock to the dividend. Thus LBR and DIV measure shocks to labor income and capital income, respectively. Similarly, RTB and TRM measure shocks to short rates and long rates that are orthogonal to stock returns and income.

News about Future Stock Returns and Labor Income

The VAR systems estimated in table 2 can be used to calculate long-run forecasts of future stock returns and future labor income growth. Revisions in these forecasts are linear combinations of shocks to the state variables, combinations that are defined by the vectors $\boldsymbol{\lambda}_h$ and $\boldsymbol{\lambda}_y$ in equations (18) and (19). Table 3 reports these vectors for both raw shocks and orthogonalized shocks. As before, monthly results are reported in panel A and annual results in panel B.

Table 3 shows that monthly shocks to LBR, DIV, RTB, and TRM all have positive effects on long-run stock return forecasts that are significant at the 10 percent level. In annual data, shocks to RVW and DIV have a significant effect on long-run stock return forecasts. In both monthly and annual data, the main shock driving long-run forecasts of income growth is the current innovation to income, but innovations to TRM also have some positive effect. If labor income

TABLE 3

NEWS ABOUT FUTURE MARKET RETURNS AND LABOR INCOME: ELEMENTS OF VECTORS λ_h AND λ_y

A. MONTHLY, 1952–90

		Shocks to				
Vector	Orthogonalized?	RVW	LBR	DIV	RTB	TRM
λ_h'	No	.001	.349	267.2	33.51	46.01
		(.026)	(.170)	(32.38)	(17.36)	(23.22)
λ_y'	No	−.021	1.140	−39.26	13.98	27.79
		(.017)	(.118)	(22.04)	(12.03)	(15.10)
λ_h'	Yes	−.922	.068	.320	−.126	.207
		(.109)	(.024)	(.041)	(.105)	(.105)
λ_y'	Yes	.114	.129	−.049	−.161	.125
		(.076)	(.016)	(.028)	(.075)	(.068)

B. ANNUAL, 1871–1990

		Shocks to			
Vector	Orthogonalized?	RVW	GNP	DIV	TRM
λ_h'	No	.258	.497	9.311	−2.293
		(.131)	(.393)	(3.546)	(2.204)
λ_y'	No	.112	1.391	1.961	2.063
		(.060)	(.244)	(1.665)	(1.161)
λ_h'	Yes	−.214	.159	.408	−.152
		(.124)	(.106)	(.149)	(.146)
λ_y'	Yes	.104	.380	.069	.136
		(.077)	(.066)	(.067)	(.077)

NOTE.—Standard errors are in parentheses.

growth were unforecastable, current labor income growth would have a weight of one in the vector λ_y and all other variables would have weights of zero; this hypothesis can be rejected at conventional significance levels.

When the VAR innovations are orthogonalized and scaled, a somewhat different pattern emerges. The first element of λ_h now becomes −0.92 in the monthly system, indicating that 92 percent of a stock return innovation is reversed in the long run. In the raw system this mean reversion is obscured because it operates through the negative correlation of the dividend yield and the contemporaneous market return.[10] The standard error for the first element of λ_h is 0.11, so

[10] Campbell (1991) discusses the mean reversion implied by a dividend yield forecasting equation. Note that the concept of mean reversion used here is a multivariate one. Stock returns are said to be mean-reverting if stock return innovations with respect to a multivariate information set are negatively correlated with revisions in expectations of future returns, based on the same information set. Campbell (1991) shows that stock returns can be mean-reverting in this sense even if they are not mean-reverting in the univariate sense of Fama and French (1988*b*) or Poterba and Summers (1988).

one can reject at the 5 percent level the hypothesis that less than 70 percent of a stock return innovation is reversed in the long run.

The importance of other shocks can now be judged by the size of their λ_h coefficients, since all shocks have been scaled to have the same variance. Positive shocks to monthly labor income have a statistically significant but very small positive effect on long-run stock return forecasts. Short rate innovations have a small and insignificant negative effect, long rate innovations have a somewhat larger and marginally significant positive effect, and dividend innovations have a positive effect that is larger again and strongly statistically significant. Thus positive shocks to labor income, capital income, and the long-term interest rate are associated with increased expected stock returns.

In annual data, the estimate of stock market mean reversion is much smaller: the first element of the orthogonalized λ_h vector is only -0.21 with a standard error of 0.12. The effect of dividend income on stock returns, however, is stronger than in monthly data. These results reflect the fact that annual variation in dividend yields is more strongly affected by movements in dividends, and less strongly affected by market returns, than monthly variation in dividend yields.

In the orthogonalized system, the coefficients defining λ_y tend to be smaller than the coefficients defining λ_h. This reflects the fact that long-run labor income forecasts are less volatile than long-run market return forecasts. (Since the orthogonalized shocks have the same variances and zero covariances, the variance of the forecast revisions is just the sum of squared coefficients in λ_h and λ_y.) Shocks to RVW, LBR, RTB, and TRM are about equally important, but RTB has a negative sign and the other variables have positive signs. In annual data, GNP and TRM are the important variables.

Table 4 reports the variances, covariances, and correlations of four variables: the current stock index return $\mathbf{e1}'\epsilon_{t+1}$, news about future stock returns $\lambda_h'\epsilon_{t+1}$, news about current and future labor income growth $\lambda_y'\epsilon_{t+1}$, and current labor income growth $\mathbf{e2}'\epsilon_{t+1}$. Variances and covariances are reported on and below the diagonal of each matrix, and correlations are reported in boldface above the diagonal. These numbers do not depend on whether the original VAR system has been orthogonalized. Several points are striking.

In the stock market variables, news about future stock returns is extremely volatile. In monthly data the variance of news about future stock returns is even slightly larger than the variance of the current return itself. (This is made possible by the fact that the VAR has multiple shocks; it would be impossible in a univariate system.) Also, news about future stock returns is strongly negatively correlated with the current return, indicating that return forecasts fall when the stock

TABLE 4

FINANCIAL AND HUMAN CAPITAL RISK: COVARIANCES AND CORRELATIONS OF NEWS VARIABLES

A. MONTHLY, 1952–90

	Current RVW $e1'\epsilon_{t+1}$ (1)	Future RVW $\lambda_h'\epsilon_{t+1}$ (2)	Current and Future LBR $\lambda_y'\epsilon_{t+1}$ (3)	Current LBR $e2'\epsilon_{t+1}$ (4)
$e1'\epsilon_{t+1}$	17.04	**−.915**	**.422**	**.169**
$\lambda_h'\epsilon_{t+1}$	−15.71	17.29	**−.242**	**−.088**
$\lambda_y'\epsilon_{t+1}$	1.950	−1.128	1.256	**.541**
$e2'\epsilon_{t+1}$	.360	−.188	.313	.266

B. ANNUAL, 1871–1990

	Current RVW $e1'\epsilon_{t+1}$ (1)	Future RVW $\lambda_h'\epsilon_{t+1}$ (2)	Current and Future GNP $\lambda_y'\epsilon_{t+1}$ (3)	Current GNP $e2'\epsilon_{t+1}$ (4)
$e1'\epsilon_{t+1}$	273.2	**−.420**	**.246**	**.130**
$\lambda_h'\epsilon_{t+1}$	−58.48	71.10	**.213**	**.255**
$\lambda_y'\epsilon_{t+1}$	28.38	12.52	48.74	**.923**
$e2'\epsilon_{t+1}$	9.595	9.591	28.78	19.94

NOTE.—Correlations are in boldface above the diagonal.

market rises. This phenomenon is particularly important in monthly data, reflecting the fact that the dividend yield forecasts future stock returns and its short-run movements are largely driven by current stock returns.

In the labor income variables, news about current and future labor income is positively correlated with the current stock return, particularly in monthly data. This correlation arises from the fact that when the market rises the dividend yield falls, increasing forecasts of future labor income growth. Also, news about current and future labor income is substantially more volatile than current labor income growth, reflecting the forecastability and positive serial correlation of the income growth process. News about current and future labor income has a positive correlation with current labor income growth: this correlation is .54 in monthly data but .92 in annual data. Current income is an important signal of long-run prospects, but other information is also relevant in at least the monthly data.

One can put together the stock market and labor income variables in table 4 to calculate the moments of the return on human capital. The human capital return is just $(\lambda_y' - \lambda_h')\epsilon_{t+1}$, the news about current and future income adjusted for news about discount rates. The variance of the human capital return is then the variance of labor income news (1.256 in monthly data), plus the variance of discount rate news (17.29), minus twice the covariance between them (-2×-1.128), for a total of 20.8, which is even larger than the variance of the stock market. Most of the variability of the human capital return comes from news about future stock returns, so it should not be surprising that the human capital return has a correlation of .94 with the stock market return in monthly data. In annual data, news about future stock returns is somewhat less important, so the variance of the human capital return is smaller than the variance of the stock market at 94.8, and the correlation between human and financial capital returns is .54.

These results contrast with the claim of Fama and Schwert (1977*b*) that human capital returns are very smooth and almost uncorrelated with the returns on stock portfolios. The reason for the difference is that Fama and Schwert use current labor income growth as a proxy for the return on human capital. Column 4 of table 4 shows that current labor income growth indeed has a small variance and only very weak correlation with the stock market. Allowing for forecastability of labor income growth, as in column 3 of table 4, slightly increases both the variance of the series and its correlation with the stock market; allowing for changing discount rates increases the variance and correlation much more dramatically.[11]

Alternative Specifications

All the results reported so far are based on one particular model specification for monthly data and a similar specification for annual data. It is important to check whether the results are robust to plausible variations in the model.

One obvious variation is to increase the lag length of the VAR, within the constraints imposed by parsimony. In a three-lag monthly VAR estimated over the postwar period, the estimate of long-run mean reversion in stock returns is -0.87 with a standard error of 0.09, very little different from the one-lag estimate of -0.92 with a standard error of 0.11. The main effects of increasing the lag length are that LBR no longer enters as a significant forecaster of long-run stock returns and that TRM no longer enters as a significant fore-

[11] Black (1987, chap. 6) and Baxter and Jermann (1994) also argue for a strong positive correlation between human and financial capital returns. As a benchmark case, Baxter and Jermann use a simple macroeconomic model in which the returns on human and financial capital are perfectly correlated.

caster of long-run labor income growth. The relative volatilities and correlations of the news variables in table 4 are insensitive to lag length. The annual results hold up in a similar manner when a two-lag VAR is estimated.

As another way to explore the lower-frequency characteristics of the data, one can time-aggregate the postwar monthly data into quarterly data and estimate a quarterly VAR system. This also has little effect on the results. The estimate of long-run mean reversion in stock returns is the same in a one-lag quarterly VAR as in a three-lag monthly VAR, and news about future stock returns remains extremely volatile (although now slightly less volatile than the current stock return) and negatively correlated with the current stock return.

I have also explored adding other variables to the VAR system. In preliminary work with monthly data, I estimated a larger system including the five variables used in the benchmark model plus the default spread and the small stock return. The coefficients defining λ_h and λ_y and the relative volatilities of news variables were similar to those reported in tables 3 and 4.

Cochrane (1994) has shown that the log ratio of nondurables and services consumption to GNP is a good forecaster of GNP growth in quarterly postwar data. Similarly, Campbell (1987*a*) has used the difference between total disposable income and a multiple of nondurables and services consumption to forecast the change in disposable labor income in a postwar quarterly VAR system. I have therefore estimated a quarterly VAR including the log ratio of nondurables and services consumption to labor income along with the financial variables used in the benchmark model.

The consumption/income ratio helps to forecast the yield spread TRM and is forecasted by the dividend yield DIV, but otherwise does not interact significantly with the other variables in the system. The estimated mean reversion of stock returns and the volatility of news about future stock returns increase slightly relative to the quarterly VAR that omits the consumption/income ratio; the properties of news about future labor income are little affected. There seem to be two main reasons why adding the consumption/income ratio has little effect on the behavior of the VAR system. First, consumption is a less powerful forecaster of labor income growth than of GNP growth. Second, the financial variables used here capture the predictability of income growth and stock returns so that macroeconomic variables (beyond the history of income growth itself) do not have marginal predictive power. Stock and Watson (1989, 1990) also find that financial variables tend to drive out macroeconomic variables in forecasting the state of the economy.

VI. Implications for Asset Pricing

A First Look at the Cross Section

I now turn to the cross-sectional aspects of the data. Column 1 of table 5 reports the mean excess log return on each stock portfolio over the 1-month Treasury bill rate. Column 2 reports the mean excess log return adjusted for Jensen's inequality by adding one-half the own variance of the log return. As before, panel A gives monthly and panel B gives annual results. The units in the table are percentage points per month (panel A) or per year (panel B).

The table shows several well-known facts about average asset returns. First, the average excess return on the value-weighted stock index has been large, over 0.5 percent at a monthly rate in the monthly data and over 5 percent at an annual rate in the annual data.[12] Second, small stocks have had a higher average return than large stocks, as shown both by the higher return of the equal-weighted index and by the pattern of returns on size decile portfolios. Third, bonds have had much lower returns than stocks: none of the monthly Ibbotson bond portfolios has an average excess return over 1 percent at an annual rate, and long-term bonds have a negative average excess return in the annual data set. Finally, the annual data show that average excess returns on gold have been even lower than those on bonds.

Columns 3–5 of table 5 show the covariances of each portfolio with underlying sources of risk: the return on the value-weighted stock index (V_{ia}), news about future labor income (V_{iy}), and news about future stock index returns (V_{ih}). The traditional CAPM prices assets using only the V_{ia} column, whereas the intertemporal model also uses the V_{iy} and V_{ih} columns. The covariances are all reported in units that match the excess return units in columns 1 and 2 of the table. That is, the covariances of natural variables are multiplied by 100 since the mean excess returns have been multiplied by 100 to express them in percentage points. The variances and covariances here are thus 100 times smaller than those reported in tables 2 and 4.

Table 5 shows some striking facts about the risk characteristics of stock and bond returns. First, the covariances of stock and bond returns with the aggregate stock market, shown in column 3, line up roughly with the pattern of average asset returns. Small stocks have larger V_{ia} than large stocks, stocks have larger V_{ia} than bonds, and in

[12] The annual equity premium reported here is slightly smaller than that in Mehra and Prescott (1985) because I use the commercial paper rate throughout the annual data set whereas Mehra and Prescott splice together a commercial paper rate and a Treasury bill rate.

TABLE 5

UNCONDITIONAL RISK AND RETURN: A SUMMARY

Portfolio	$\overline{er}_i$ (1)	$\overline{er}_i + (V_{ii}/2)$ (2)	V_{ia} (3)	V_{iy} (4)	V_{ih} (5)
		A. Monthly, 1952–90			
EW	.562	.690	.184	.022	−.170
VW	.451	.541	.169	.019	−.156
Size 1	.641	.850	.190	.022	−.178
Size 2	.644	.812	.188	.023	−.176
Size 3	.595	.757	.191	.023	−.176
Size 4	.594	.739	.189	.023	−.174
Size 5	.533	.671	.187	.022	−.172
Size 6	.554	.681	.183	.021	−.168
Size 7	.547	.669	.185	.021	−.169
Size 8	.542	.656	.182	.021	−.168
Size 9	.491	.592	.173	.020	−.161
Size 10	.387	.472	.158	.019	−.145
PET	.548	.683	.152	.017	−.145
FRE	.420	.535	.174	.018	−.166
CDR	.408	.546	.182	.022	−.164
BAS	.421	.534	.180	.021	−.166
FTB	.645	.730	.144	.016	−.134
CNS	.350	.513	.196	.020	−.183
CAP	.459	.588	.173	.023	−.155
TRN	.309	.481	.198	.023	−.183
UTI	.450	.511	.109	.012	−.102
TEX	.435	.580	.180	.019	−.162
SVS	.445	.624	.191	.022	−.174
LSR	.590	.776	.208	.023	−.188
LTG	−.009	.026	.028	.002	−.034
STG	.065	.076	.012	.002	−.014
CRP	.018	.048	.030	.003	−.035
		B. Annual, 1871–1990			
VW	3.501	5.197	2.525	.342	−.817
LTG	−.322	−.142	.231	.065	−.133
GLD	−2.349	−1.429	−.314	−.046	−.079

NOTE.—All variables are measured in percentage points, at a monthly rate in panel A and an annual rate in panel B.

annual data V_{ia} for gold is negative. Second, the covariances of returns with labor income news, shown in column 4, are all very small, typically an order of magnitude smaller than the stock market covariances. Third, the covariances with news about future returns, shown in column 5, are negative and almost as large in absolute value as the stock market covariances V_{ia}.

Finally, there is a strong negative cross-sectional correlation between V_{ia} and V_{ih}. Assets with a large positive V_{ia} tend to have a large negative V_{ih}. This fact is illustrated in figure 1, which plots V_{ih} against

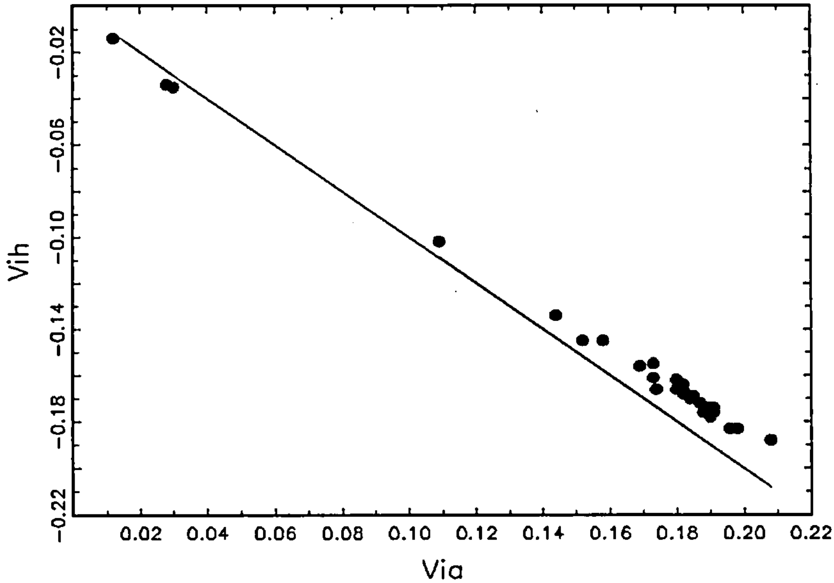

FIG. 1.—Covariance with news about future stock returns against covariance with the current stock return. This figure uses cols. 5 and 3 of table 5.

V_{ia} using the numbers in columns 4 and 5 of table 5. The solid line in the figure is a negative 45° line; it is apparent that the ratio V_{ih}/V_{ia} is approximately constant and negative and has an absolute value slightly less than one. This cross-sectional relationship reflects the mean reversion of stock returns discussed earlier. Since a positive stock index return today is associated with lower expectations of returns in the future, assets that covary positively with today's return tend to covary negatively with expectations of future returns.

The Equity Premium and the Coefficient of Relative Risk Aversion

The cross-sectional patterns summarized in table 5 can be combined with the time-series properties of the data summarized in tables 2, 3, and 4 to estimate the intertemporal model of this paper. Before we embark on this task, however, it is worth developing intuition by looking just at the value-weighted stock index return.

Friend and Blume (1975) used the traditional CAPM and the properties of the value-weighted stock return to estimate the coefficient of relative risk aversion γ. Recall that the model of this paper is

$$\overline{er}_i + \frac{V_{ii}}{2} = \gamma(1 - \nu)V_{ia} + \gamma\nu V_{iy} + [\gamma(1 - \nu) - 1]V_{ih}, \qquad (27)$$

where $\overline{er}_i \equiv E[r_{i,t+1} - r_{f,t+1}]$. The traditional CAPM is the special case in which human capital is ignored by setting $\nu = 0$ and changing expected returns are ignored by setting $V_{ih} = 0$. In this case (27) becomes $\overline{er}_i + (V_{ii}/2) = \gamma V_{ia}$, so γ should equal the average log excess return adjusted for Jensen's inequality in column 2 of table 5 divided by the stock market covariance in column 3 of table 5. If one uses the value-weighted index row in panel A of table 5, this gives an estimate of γ of $0.541/0.168 = 3.2$. The same row in panel B gives a fairly similar estimate of $\gamma = 2.1$.

More recently, Mehra and Prescott (1985) and others have emphasized that a consumption-based approach implies much larger values of γ. Yet it is unclear why the consumption-based approach and the Friend and Blume approach give such different answers. Table 6 presents some back-of-the-envelope calculations to address this issue. The table takes the point estimates from the value-weighted index row of table 5 and uses them to calculate the value of γ implied by different assumptions about ν (the share of human capital) and V_{ih} (the mean reversion of stock returns).

The two rows in each panel of table 6 correspond to two assumptions about the predictability of market returns. The first row sets $V_{ih} = 0$, which corresponds to the traditional assumption that the market return is unforecastable (or at least that any revisions in return forecasts are uncorrelated with the contemporaneous market return). The second row sets V_{ih} equal to the estimated value from table 5, -0.156 monthly or -0.817 annually. The four columns in table 6 correspond to values of ν ranging from zero (the traditional approach that ignores human capital) to one (the opposite extreme that ignores the stock market). A reasonable value of ν is two-thirds, since this is roughly the share of labor in national output.

TABLE 6

FITTING THE EQUITY PREMIUM: A BACK-OF-THE-ENVELOPE CALCULATION

	ν			
V_{ih}	0	1/3	2/3	1
	A. Monthly, 1952–90			
0	3.2	4.6	7.8	28
Estimated	31	26	23	20
	B. Annual, 1871–1990			
0	2.1	2.9	4.9	15
Estimated	2.6	3.5	5.5	13

NOTE.—This table shows the value of γ implied by different values of V_{ih} and ν and the numbers given in the VW row of table 5.

Table 6 uses the formula

$$\gamma = \frac{\overline{er}_i + (V_{ii}/2) + V_{ih}}{(1 - \nu)(V_{ia} + V_{ih}) + \nu V_{iy}}, \tag{28}$$

which follows directly from (27). The table shows that estimates of γ as low as Friend and Blume's can be obtained only by ignoring both human capital and stock market mean reversion. In monthly data, γ changes most dramatically when one allows for mean reversion; for any value of ν, γ exceeds 20 when mean reversion is estimated rather than assumed to be zero. Changing ν has a smaller effect except when ν is very close to one. In annual data there is less estimated mean reversion, and the main effects on γ come from taking account of human capital.

To understand these findings, it is helpful to think about the two extreme cases in which $\nu = 0$ and $\nu = 1$. When $\nu = 0$, (27) implies that $\overline{er}_i + (V_{ii}/2) = \gamma(V_{ia} + V_{ih}) - V_{ih}$. Since V_{ih} is negative and (in monthly data) is almost as large in absolute value as V_{ia}, the sum $V_{ia} + V_{ih}$ is small, requiring a large γ to fit the equity premium. The mean reversion of the stock market makes its long-run risk much smaller than its short-run risk, so a large coefficient of risk aversion is required to explain a large equity premium. Black (1990) also emphasizes the fact that mean reversion can dramatically alter the relationship between risk aversion and the equity premium.

When $\nu = 1$, (27) implies that $\overline{er}_i + (V_{ii}/2) = \gamma V_{iy} - V_{ih}$. But V_{iy} is small, so again a large γ is required to fit the equity premium. To understand this case, rewrite the equity premium formula as $\overline{er}_i + (V_{ii}/2) = \gamma(V_{iy} - V_{ih}) + (\gamma - 1)V_{ih}$. The risk premium is γ times the covariance with the return on human capital, $V_{iy} - V_{ih}$, plus $\gamma - 1$ times the covariance with news about future investment opportunities, V_{ih}. When there is no mean reversion in returns, $V_{ih} = 0$ and the covariance with human capital is just V_{iy}, which is small because labor income growth is smooth. When there is mean reversion in returns, then the covariance with human capital is large but is offset by the long-run effects of the mean reversion. Either way the risk of stock market investment is small and a large coefficient of risk aversion is needed to explain a large equity premium.

Fama and Schwert (1977*b*) have argued that Mayers's (1972) version of the CAPM, which allows for human capital, does not differ greatly from the standard CAPM in its empirical predictions. Their argument is based on the empirical claim that $V_{iy} \approx 0$ for all assets. If one sets $V_{iy} = 0$ and also $V_{ih} = 0$ (since Fama and Schwert do not allow for stock market mean reversion), then (28) becomes $\gamma = [\overline{er}_i + (V_{ii}/2)]/[(1 - \nu)V_{ia}]$. In this case estimates of risk aversion depend on mean returns and covariances with the aggregate stock market, but they also depend on ν, the share of human capital in aggregate wealth. Fama and Schwert miss this point because they work with the beta representation of the model and do not consider the relation between the expected excess return on the aggregate stock market and the underlying risk aversion of investors.

System Estimation and the Pattern of Risk Prices

With this introduction, I now report estimates of the full unconditional asset pricing model, using all 25 portfolios monthly and three portfolios annually.[13] The model is estimated with and without intertemporal restrictions. In the intertemporally restricted specification the parameter ν is fixed a priori at zero, two-thirds, or one, and the risk aversion coefficient γ is estimated. In the monthly data the 25 mean portfolio returns then identify one parameter, and there are 24 overidentifying restrictions. In the unrestricted five-factor specification the factor risk prices are freely estimated, so with 25 portfolios there are 20 overidentifying restrictions. In the annual data there are only three portfolios, so the intertemporal models have two overidentifying restrictions and the unrestricted four-factor model is unidentified. The estimation results are summarized in table 7.

In the monthly data of table 7 (panel A), the estimated coefficient of risk aversion ranges from 16 when $\nu = 0$ to 21 when $\nu = 2/3$. These estimates have very large standard errors, so only the $\nu = 0$ estimate is significantly different from zero at the 5 percent level. Table 7 also reports the risk prices for orthogonalized factors. Only the price of stock market risk is precisely estimated; it ranges between 2.8 and 4.0, with standard errors around one. Presumably this reflects the fact that most of the portfolios have much larger covariances with the stock market than with the other factors, enabling this risk price to be pinned down more precisely. The price of stock market risk is Friend and Blume's estimate of the coefficient of risk aversion, but the intertemporal model implies greater risk aversion for the reasons already discussed.

In the intertemporal model, the other factors have risk prices that are related to their forecasting role. These risk prices are similar in magnitude to the price of stock market risk, although much less pre-

[13] The reported results are based on three iterations of GMM. Starting values for the parameters are as follows: ordinary least squares estimates are used for the VAR coefficients, sample mean asset returns are used for the vector μ, cross-sectional regression estimates are used for unrestricted factor risk prices, and the γ estimates from table 6 are used for the restricted models. The initial weighting matrix is optimal conditional on the starting values of the parameters.

TABLE 7

ESTIMATES OF RISK AVERSION AND RISK PRICES

A. MONTHLY, 1952–90

Portfolios (Restricted?)	ν	γ	Risk Prices for: RVW	LBR	DIV	RTB	TRM
22 stocks, 3 bonds (yes)	0	15.61	3.903	.758	3.893	−4.858	4.401
		(7.368)	(1.153)	(.615)	(2.444)	(2.126)	(2.054)
22 stocks, 3 bonds (yes)	⅔	21.21	3.406	2.202	1.083	−4.256	3.694
		(11.25)	(1.090)	(1.324)	(1.164)	(1.969)	(2.035)
22 stocks, 3 bonds (yes)	1	17.66	2.840	2.185	−1.228	−3.885	2.893
		(11.64)	(.986)	(1.604)	(.404)	(1.980)	(2.004)
22 stocks, 3 bonds (no)	N/A	N/A	3.075	−10.35	−1.227	−4.046	5.097
			(1.315)	(4.339)	(4.307)	(2.612)	(2.634)

B. ANNUAL, 1871–1990

Portfolios (Restricted?)	ν	γ	Risk Prices for: RVW	GNP	DIV	TRM
Stocks, bonds, gold (yes)	0	2.683	2.355	.291	.661	−.307
		(1.102)	(.860)	(.235)	(.503)	(.285)
Stocks, bonds, gold (yes)	⅔	5.305	2.107	1.542	.494	.229
		(2.442)	(.806)	(.783)	(.530)	(.298)
Stocks, bonds, gold (yes)	1	9.657	1.608	3.721	.076	.965
		(5.943)	(.720)	(2.408)	(.704)	(.755)

NOTE.—Standard errors are in parentheses.

cisely estimated. Labor income has a positive risk price that increases with the importance of human capital, since labor income is a strong forecaster of future labor income growth. The dividend yield has a positive risk price when ν is small, since a high dividend yield forecasts high future stock returns. This risk price turns negative when ν is large, since a high dividend yield forecasts slow future labor income growth. The short rate has a negative risk price for all values of ν, since a high short rate forecasts low future stock returns and slow future labor income growth. Finally, the long rate has a positive risk price for all values of ν, since a high long rate forecasts high future stock returns and rapid future labor income growth.

To see more formally how the parameter γ and the vectors $\boldsymbol{\lambda}_h$ and $\boldsymbol{\lambda}_y$ determine the risk prices associated with the factors in the intertemporal model, rewrite equation (20) as

$$\overline{er}_i + \frac{V_{ii}}{2} = \{\gamma(1-\nu) + \gamma\nu\lambda_{y1} + [\gamma(1-\nu) - 1]\lambda_{h1}\}V_{i1} + \sum_{k=2}^{K}\{\gamma\nu\lambda_{yk} + [\gamma(1-\nu) - 1]\lambda_{hk}\}V_{ik}. \tag{29}$$

It is easiest to understand this formula by considering the special cases $\nu = 0$ and $\nu = 1$. When $\nu = 0$, (29) becomes

$$\begin{aligned}\overline{er}_i + \frac{V_{ii}}{2} &= [\gamma + (\gamma - 1)\lambda_{h1}]V_{i1} + \sum_{k=2}^{K} (\gamma - 1)\lambda_{hk}V_{ik} \\ &\approx \gamma(1 + \lambda_{h1})V_{i1} + \sum_{k=2}^{K} \gamma\lambda_{hk}V_{ik},\end{aligned} \tag{30}$$

where the approximate equality holds for large γ. Equation (30) implies that the risk price for the first factor (the stock market return) is approximately $\gamma(1 + \lambda_{h1})$. This is much less than γ when λ_{h1} is negative, as it is in the orthogonalized-factor row of table 3. This is another way to see the difficulty with the Friend and Blume calculation of risk aversion. The risk prices for the other factors are approximately $\gamma\lambda_{hk}$. Given large γ and the orthogonalized $\boldsymbol{\lambda}_h$ estimates of table 3, this means that several different orthogonalized factors have risk prices that have the same order of magnitude as the stock market risk price.

When $\nu = 1$, the stock market factor loses its unique role and equation (29) becomes

$$\overline{er}_i + \frac{V_{ii}}{2} = \sum_{k=1}^{K} (\gamma\lambda_{yk} - \lambda_{hk})V_{ik}. \tag{31}$$

For large γ, the risk prices become approximately proportional to the elements of the vector $\boldsymbol{\lambda}_y$ that forecasts labor income. The table 3 estimates of $\boldsymbol{\lambda}_y$ imply that in this case too, several different orthogonalized factors have risk prices of comparable magnitude.

In the unrestricted factor model, the risk prices for RVW, RTB, and TRM are similar to those in the intertemporal models. The risk price for DIV is negative, contrary to the intertemporal models with low ν, but this risk price is very imprecisely estimated. More seriously, the risk price for LBR is significantly negative in the unrestricted factor model whereas it is always positive in the intertemporal models, particularly when ν is high. Chi-squared tests of the overidentifying restrictions reject the unrestricted factor model at the 5.9 percent level and reject the three intertemporal models at the 4.9 percent level when $\nu = 0$, the 4.3 percent level when $\nu = 2/3$, and the 2.9 percent level when $\nu = 1$. This pattern of results reflects the mispricing of labor income risk.

In the annual data set, there are not enough portfolios to estimate an unrestricted four-factor model. Accordingly, only restricted intertemporal models are estimated in table 7; the pattern of results is quite similar to that in the monthly data, except that estimated risk aversion coefficients are smaller. None of the models' overidentifying restrictions are rejected at even the 30 percent level.

Why Do Different Assets Have Different Mean Returns?

The contribution of orthogonalized factors to the cross-sectional pattern of mean returns depends not only on factor risk prices but also on the cross-sectional pattern of assets' covariances with factors. Since the factors have been orthogonalized, the covariance of the real value-weighted index return with the other factors is zero. The covariance of the excess value-weighted index return is not exactly zero since the commercial paper rate is not included in the VAR information set, but it is always very close to zero. By construction, then, the other factors play little role in explaining the excess return on the stock market as a whole. The individual stock portfolios move closely with the aggregate stock market index, and thus for these portfolios too the other factors play a secondary role. Bond portfolios behave somewhat differently, covarying more strongly with the interest rate factors than with the stock market factor. As one would expect, the two long-term bond portfolios covary more strongly with the long rate factor, and the short-term bond portfolio covaries more strongly with the short rate factor.

Table 8 combines the portfolio factor covariances with a representative set of factor risk prices shown in table 7. (The risk prices from the intertemporally restricted model with $\nu = 2/3$ are used.) Thus table 8 shows the contribution of each factor to the expected excess return on each asset. Column 8 of table 8 shows the pricing error for each asset, that part of the sample average excess return on the asset that is not explained by its sample covariances with the factors and the sample estimates of risk prices.

It is immediately obvious that the stock market factor is far more important than any of the other factors in determining expected returns on stock portfolios. Labor income risk increases small stock returns and reduces large stock returns, but this effect is not important enough to explain the size effect in sample average returns. For bond portfolios the important factors are the stock market, the short rate, and the long rate. The first two factors raise bond returns and the last reduces bond returns; since long-term bonds have greater covariances with long rates, this helps to explain the low or negative average term premia over the sample period. Overall, table 8 shows that much of the cross-sectional variation in asset returns can be explained by the stock market covariance emphasized in the traditional CAPM. Figure 2 gives a visual impression of this by plotting sample

TABLE 8

FACTOR CONTRIBUTIONS TO EXPECTED RETURNS

A. MONTHLY, 1952–90

Portfolio	$\overline{er}_i$ (1)	$\overline{er}_i + (V_{ii}/2)$ (2)	RVW (3)	LBR (4)	DIV (5)	RTB (6)	TRM (7)	Error (8)
EW	.562	.690	.615	−.001	.001	.003	.004	.068
VW	.451	.541	.565	−.010	.001	−.010	.014	−.019
Size 1	.641	.850	.632	.010	−.005	−.026	.009	.230
Size 2	.644	.812	.626	.011	−.004	−.004	.002	.181
Size 3	.595	.757	.636	.013	.001	−.004	.013	.098
Size 4	.594	.739	.632	.001	.005	.015	.003	.083
Size 5	.533	.671	.623	.001	.003	.013	−.000	.031
Size 6	.554	.681	.609	−.004	.005	.008	.004	.059
Size 7	.547	.669	.616	−.010	.008	.012	.007	.036
Size 8	.542	.656	.608	−.013	.005	.017	−.006	.045
Size 9	.491	.592	.580	−.009	.002	.013	−.012	.018
Size 10	.387	.472	.528	−.009	−.002	−.006	.036	−.075
PET	.548	.683	.507	−.016	−.018	−.065	.061	.214
FRE	.420	.535	.584	−.026	−.004	.033	−.053	.001
CDR	.408	.546	.607	.004	.009	−.017	.054	−.111
BAS	.421	.534	.604	−.010	−.003	−.010	.038	−.085
FTB	.645	.730	.484	−.017	.003	.030	−.029	.259
CNS	.350	.513	.651	−.019	.006	−.020	−.027	−.078
CAP	.459	.588	.577	−.013	.003	.014	.101	−.094
TRN	.309	.481	.660	.009	.000	−.021	.021	−.188
UTI	.450	.511	.366	−.010	.003	.063	−.057	.146
TEX	.435	.580	.600	−.026	.018	.010	−.006	−.016
SVS	.445	.624	.636	−.004	.006	−.002	.023	−.035
LSR	.590	.776	.693	−.022	.016	−.008	.022	.075
LTG	−.009	.026	.095	−.022	−.007	.154	−.178	−.016
STG	.065	.076	.040	−.011	−.005	.124	−.093	.021
CRP	.018	.048	.101	−.012	−.006	.143	−.166	−.012

B. ANNUAL, 1871–1990

Portfolio	$\overline{er}_i$ (1)	$\overline{er}_i + (V_{ii}/2)$ (2)	RVW (3)	GNP (4)	DIV (5)	TRM (6)	Error (7)
VW	3.501	5.197	5.385	.370	−.320	.069	−.307
LTG	−.322	−.142	.495	−.058	−.013	.102	−.668
GLD	−2.349	−1.429	−.659	−.000	−.160	.028	−.638

NOTE.—All variables are measured in percentage points, at a monthly rate in panel A and an annual rate in panel B. The contribution of each factor to expected returns is calculated from the intertemporal model with $\nu = 2/3$ estimated in table 7. The unexplained component of expected returns is given in the error column.

average returns in the monthly data set (from col. 2 of table 5) against covariances with the value-weighted stock index (from col. 3 of table 5). The solid line in figure 2 has a slope of 3.406, the estimated price of stock market risk from the intertemporally restricted model with $\nu = 2/3$.

Given the emphasis of this paper on human capital and intertemporal hedging, it may seem surprising that the covariance with the stock

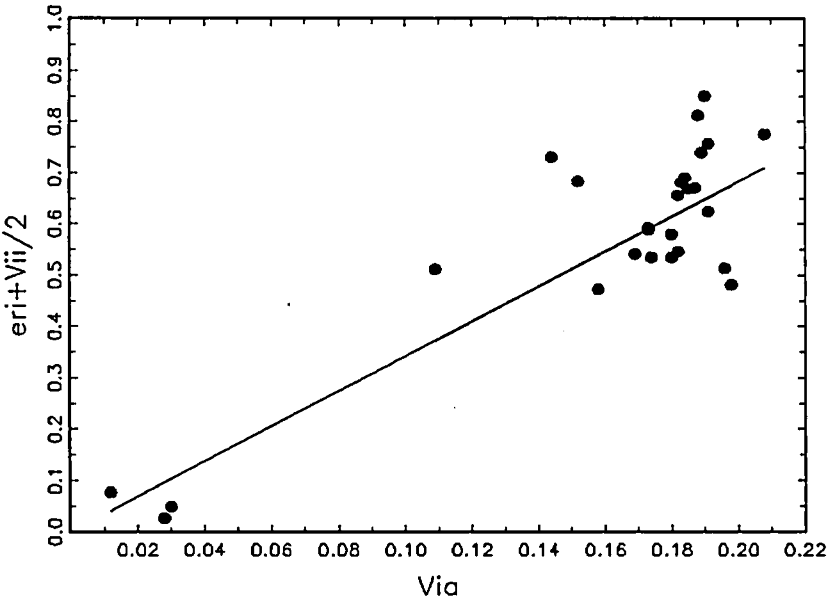

FIG. 2.—Average excess return against covariance with the current stock return. This figure uses cols. 2 and 3 of table 5.

market is so dominant in explaining the cross-sectional pattern of asset returns. This can be understood by recalling the three special cases in which the intertemporal model collapses to a logarithmic version of the static CAPM. First, the static CAPM holds if $\gamma = 1$; but the estimates of γ in table 7 are much larger than one, so this is not empirically relevant. Second, the static CAPM holds if $V_{ih} = 0$ for all assets; but the estimates of V_{ih} in table 5 are almost as large in absolute value as the estimates of V_{ia}, so this case is also not relevant. Third, the static CAPM holds if there is perfect cross-sectional correlation between V_{ih} and V_{im}.

This last case seems to describe the data remarkably well. Time-varying discount rates and smooth labor income imply a strong correlation between the returns on human and financial capital, so V_{ia} becomes a good proxy for V_{im}. And figure 1, using numbers from table 5, shows that V_{ih} is strongly negatively correlated with V_{ia}. Investors determine assets' expected returns from their covariance with an aggregate stock index not only because the stock index return is a component of the return on the market, but also because the value of human capital is correlated with the stock index and because the stock index return is the most important source of news about future investment opportunities.

Alternative Specifications

The results discussed in this section are robust to a number of changes in model specification. Adding lags to the monthly VAR, moving to a quarterly data frequency, or adding the consumption/income ratio to the quarterly VAR does not change the qualitative pattern of the results. Estimates of risk aversion γ remain large and generally imprecise (although statistically significant when $\nu = 0$), and the signs of factor risk prices are much the same as in the one-lag monthly model. The main effect of moving to quarterly data is to increase the importance of the factor DIV in explaining asset returns in the case $\nu = 0$; the risk price for DIV is 4.87 with a standard error of 1.9 in this case, and DIV helps to explain the size effect because small firms have higher covariances with DIV than large firms. The importance of DIV is even more pronounced when the consumption/income ratio is added to the system. However, none of these results changes the basic proposition that the covariance with an aggregate stock index is the primary measure of risk for the assets considered here.

I have also tried estimating the parameter ν jointly with the parameter γ instead of fixing ν beforehand. In the benchmark monthly model with one lag, ν is estimated to be 0.523 with a standard error of 0.457; thus one cannot reject the hypothesis that $\nu = 0$, but equally one cannot reject the hypothesis that $\nu = 1$. In the quarterly postwar model and the long annual data set, the estimates of ν are even less precise.

All these results are based on the implications of a heteroskedastic asset pricing model for the unconditional moments of excess returns, as explained in Section IV. I have also tested a homoskedastic asset pricing model, which imposes the extra orthogonality conditions implied by constant conditional second moments. Given the enormous body of evidence that conditional second moments vary through time, it should not be surprising that this model is very strongly rejected. Finally, I have tested the implications of the heteroskedastic model for the conditional moments of excess returns; these implications are also very strongly rejected, indicating that the model developed here does not account for the predictability of excess returns on stocks and bonds.[14]

VII. Some Implications for Consumption

In the intertemporal model the behavior of risk premia is determined only by the coefficient of relative risk aversion γ; the intertemporal elasticity of substitution σ plays no role. Conversely, equation (14) shows that the behavior of consumption is determined only by σ

[14] Campbell and Cochrane (1995) present a model that does fit the predictability of excess returns.

and not by γ. An interesting exercise is to calculate the consumption behavior implied by the estimated VAR model for different values of ν and σ.

Combining (14) with the VAR model, one can calculate the implied consumption innovation as

$$c_{t+1} - E_t c_{t+1} = [(1-\nu)\mathbf{e1}' + \nu\boldsymbol{\lambda}_y' + (1-\sigma-\nu)\boldsymbol{\lambda}_h']\boldsymbol{\epsilon}_{t+1}. \quad (32)$$

Panel A of table 9 shows the implied standard deviation of quarterly consumption innovations and their correlations with quarterly RVW and LBR, for a range of σ and ν values. For comparison the table also reports the sample moments for per capita real consumption of nondurables and services, the series most often used in empirical work on consumption-based asset pricing. Quarterly rather than monthly postwar data are used here to try to reduce the effect of measurement error on the consumption data.

As one would expect, theoretical consumption becomes smoother when σ is small, for then stock market mean reversion smooths consumption. With small σ, consumption is driven primarily by income effects, and the income effect of a 1 percent stock return is less than 1 percent if stock returns are mean-reverting. Even when $\sigma = 0$, however, theoretical consumption is still at least four times as volatile as measured consumption. When one looks at the correlations, low values of σ are necessary to get the correlation with stock returns much below one and to get a high correlation between consumption growth and labor income growth. Annual results over the period 1890–1990, reported in panel B, are qualitatively similar. These admittedly rough calculations suggest that low intertemporal substitution is necessary to match consumption behavior with asset return behavior.[15] Hall (1988) and Campbell and Mankiw (1989) have also argued for a low intertemporal elasticity of substitution on the grounds that real interest rate movements are not associated with large predictable movements in consumption.

The numbers in table 9 are less helpful in determining a plausible value for ν, the share of human capital in total wealth. A high ν reduces the volatility of consumption, but a high ν also tends to give counterfactually high correlations of consumption growth with labor income growth and (particularly) stock index returns.

VIII. Conclusion

The static CAPM still has an important place in most economists' thinking about asset returns. Does the CAPM give a good first ap-

[15] Kandel and Stambaugh (1991) make the same point by numerically solving a discrete-state asset pricing model.

TABLE 9

ACTUAL AND THEORETICAL CONSUMPTION BEHAVIOR

A. QUARTERLY, 1952–90

σ	ν = 0	1/3	2/3	1
	Standard Deviation of Consumption Innovation (Actual = .43)			
0	2.6	2.1	1.7	1.8
.5	4.5	4.4	4.6	4.8
1	7.6	7.8	8.0	8.3
2	14.5	14.7	15.0	15.3
	Correlation of Consumption and RVW Innovations (Actual = .26)			
0	.38	.52	.67	.69
.5	.96	.99	.98	.94
1	1.00	.99	.98	.95
2	.99	.98	.96	.95
	Correlation of Consumption and LBR Innovations (Actual = .47)			
0	.18	.34	.53	.64
.5	.20	.26	.30	.33
1	.18	.21	.23	.25
2	.16	.17	.18	.19

B. ANNUAL, 1890–1990

σ	ν = 0	1/3	2/3	1
	Standard Deviation of Consumption Innovation (Actual = 2.9)			
0	15.2	11.3	8.4	7.5
.5	15.6	11.8	9.0	8.0
1	17.3	13.9	11.4	10.6
2	22.9	20.4	18.8	18.2
	Correlation of Consumption and RVW Innovations (Actual = .07)			
0	.86	.82	.67	.25
.5	.97	.97	.86	.50
1	1.00	.98	.86	.58
2	.94	.87	.75	.57
	Correlation of Consumption and GNP Innovations (Actual = .37)			
0	.27	.45	.72	.93
.5	.20	.35	.56	.75
1	.13	.23	.36	.47
2	.01	.06	.11	.17

proximation to the cross-sectional pattern of returns, or should the model be abandoned? In this paper I have used a more general intertemporal asset pricing model to try to answer this question.

I have argued that the CAPM, as traditionally implemented in empirical work, is seriously flawed. Most important, it ignores time variation in expected stock returns. In monthly postwar U.S. data, the time variation in returns is large and takes the form of mean reversion, reducing the long-run risk of stock market investment relative to the short-run risk. By neglecting mean reversion, the CAPM overstates the risk of stock market investment and correspondingly understates the risk aversion coefficient needed to fit the equity premium.

The CAPM also ignores the fact that human capital is an important component of wealth. In monthly postwar U.S. data, this omission is less serious because changing expected stock returns affect the value of human capital as well as the prices of stocks and make the estimated human capital return as volatile as and highly correlated with the stock return. In a longer-run annual data set, however, time variation in stock returns is less dramatic and the human capital return is less volatile than the stock return. By ignoring human capital, the CAPM again overstates the risk of investing in stocks and other financial assets and understates the risk aversion coefficient needed to explain risk premia.

Despite these flaws, the CAPM does capture most of the variation in expected excess returns across the assets studied here. At a mechanical level, this result may not be surprising since the market is the first factor in all the multifactor models studied here. Empirically, all the stock portfolios studied here have high average excess returns and large covariances with the stock market, whereas the bond portfolios have low average excess returns and small covariances with the stock market. In the annual data set, gold has a negative average excess return and a negative covariance with the stock market. This cross-sectional variation in covariances with the stock market dwarfs the cross-sectional variation in covariances with any of the other factors, and in this limited sense the CAPM is a good approximate model of stock and bond pricing.

Thus, while the intertemporal theory does generate a multifactor model with some significant risk prices on the other factors, its main contribution is to explain why investors use covariance with an aggregate stock index to determine expected returns on assets. The aggregate stock index is relevant not only because it is a component of total wealth, but because its return is correlated with the return on human capital and with shifts in the investment opportunity set.

The insights provided by the intertemporal model do not come without costs. Most obviously, many assumptions and approximations have to be used to derive the theoretical model. There are also some more specific empirical concerns. First, the empirical implementation of the model assumes that all relevant information variables available to investors are used in the VAR system; while the results appear to be robust to reasonable changes in specification, it is always possible that important variables have been omitted from the analysis that could affect the results. Second, the model is valid in the presence of heteroskedastic asset returns only if the elasticity of intertemporal substitution is one. The results of Hall (1988) and Campbell and Mankiw (1989) and the rough calculations of Section VII suggest instead that the elasticity of intertemporal substitution is close to zero. While the intertemporal model might remain a good approximation in this case (as suggested by the results of Campbell [1993] for a homoskedastic model), it is not obvious that this is so. Third, the implications of the intertemporal model for the conditional moments of asset returns are strongly rejected, although there is only weak evidence against its implications for unconditional moments, which are the primary focus of this paper.

The approach suggested in this paper can be developed in a number of directions. The asset pricing model can be embedded in a macroeconomic model that jointly determines the return on human and financial capital. Baxter and Jermann (1994) give a simple example of this approach. The asset pricing theory can be modified to give a better account of predictable time variation in excess returns, perhaps along the lines of Campbell and Cochrane (1995).

Fama and French (1992) have recently argued that the CAPM is entirely inadequate as a description of cross-sectional asset pricing. They reach this conclusion by showing that stocks' betas are almost cross-sectionally uncorrelated with their expected returns once one controls for their market and book values. Fama and French (1993) argue that a model with five factors can account for the cross-sectional pattern of returns. The factors include portfolios that capture common variation in returns on small stocks and on stocks with high ratios of book to market value. As Fama and French admit, these factors "have no special standing in asset pricing theory" (p. 3), and their risk prices are freely estimated to fit the data.

This paper does not directly address Fama and French's findings because it uses traditional size and industry portfolios rather than portfolios grouped by size, beta, and book-to-market ratio. An interesting extension of the research in this paper will be to relate Fama and French's results to the intertemporal model used here. The intertemporal model imposes additional structure on the investigation, and this has several virtues.

First, it reduces the freedom of the researcher to search across specifications. Factors can appear in the cross-sectional asset pricing model only if they are innovations in variables that help to forecast market returns and labor income. A small-stock return, for example, can be a priced factor only if some variable such as the small-stock dividend yield has forecasting power for returns and income. This discipline reduces "data-snooping" bias (Lo and MacKinlay 1990) since variables that spuriously explain the cross section are unlikely to be the same as variables that spuriously forecast the time series.

Second, the intertemporal model derives factor risk prices from underlying characteristics of the economy rather than estimating them freely. MacKinlay (1995) argues that multifactor models can account for observed deviations from the CAPM only if they have unreasonably high risk prices for the extra factors. MacKinlay uses intuition to judge what is a reasonable factor risk price; this paper offers a more formal approach. Ultimately, a satisfying model of risk and return must explain the magnitudes of the rewards that investors receive for bearing different kinds of risk. This paper explores one simple framework in which these rewards can be understood.

References

Baxter, Marianne, and Jermann, Urban. "The International Diversification Puzzle Is Worse than You Think." Manuscript. Charlottesville: Univ. Virginia, Dept. Econ., 1994.

Black, Fischer. *Business Cycles and Equilibrium.* New York: Blackwell, 1987.

———. "Mean Reversion and Consumption Smoothing." *Rev. Financial Studies* 3, no. 1 (1990): 107–14.

Breeden, Douglas T. "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities." *J. Financial Econ.* 7 (September 1979): 265–96.

Campbell, John Y. "Does Saving Anticipate Declining Labor Income? An Alternative Test of the Permanent Income Hypothesis." *Econometrica* 55 (November 1987): 1249–73. (*a*)

———. "Stock Returns and the Term Structure." *J. Financial Econ.* 18 (June 1987): 373–99. (*b*)

———. "A Variance Decomposition for Stock Returns." *Econ. J.* 101 (March 1991): 157–79.

———. "Intertemporal Asset Pricing without Consumption Data." *A.E.R.* 83 (June 1993): 487–512.

Campbell, John Y., and Cochrane, John H. "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior." Working Paper no. 4995. Cambridge, Mass.: NBER, January 1995.

Campbell, John Y., and Mankiw, N. Gregory. "Consumption, Income, and Interest Rates: Reinterpreting the Time Series Evidence." In *NBER Macroeconomics Annual 1989,* edited by Olivier J. Blanchard and Stanley Fischer. Cambridge, Mass.: MIT Press, 1989.

Campbell, John Y., and Shiller, Robert J. "Stock Prices, Earnings, and Expected Dividends." *J. Finance* 43 (July 1988): 661–76.

Chan, K. C.; Chen, Nai-fu; and Hsieh, David A. "An Exploratory Investiga-

tion of the Firm Size Effect." *J. Financial Econ.* 14 (September 1985): 451–71.
Chen, Nai-fu. "Financial Investment Opportunities and the Macroeconomy." *J. Finance* 46 (June 1991): 529–54.
Chen, Nai-fu; Roll, Richard; and Ross, Stephen A. "Economic Forces and the Stock Market." *J. Bus.* 59 (July 1986): 383–403.
Cochrane, John H. "A Cross-Sectional Test of a Production-Based Asset Pricing Model." Working Paper no. 4025. Cambridge, Mass.: NBER, March 1992.
———. "Permanent and Transitory Components of GNP and Stock Prices." *Q.J.E.* 109 (February 1994): 241–65.
Epstein, Larry G., and Zin, Stanley E. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework." *Econometrica* 57 (July 1989): 937–69.
———. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis." *J.P.E.* 99 (April 1991): 263–86.
Estrella, Arturo, and Hardouvelis, Gikas A. "The Term Structure as a Predictor of Real Economic Activity." *J. Finance* 46 (June 1991): 555–76.
Fama, Eugene F. "Multiperiod Consumption-Investment Decisions." *A.E.R.* 60 (March 1970): 163–74.
———. "Efficient Capital Markets: II." *J. Finance* 46 (December 1991): 1575–1617.
Fama, Eugene F., and French, Kenneth R. "Dividend Yields and Expected Stock Returns." *J. Financial Econ.* 22 (October 1988): 3–25. (*a*)
———. "Permanent and Temporary Components of Stock Prices." *J.P.E.* 96 (April 1988): 246–73. (*b*)
———. "Business Conditions and Expected Returns on Stocks and Bonds." *J. Financial Econ.* 25 (November 1989): 23–49.
———. "The Cross-Section of Expected Stock Returns." *J. Finance* 47 (June 1992): 427–65.
———. "Common Risk Factors in the Returns on Stocks and Bonds." *J. Financial Econ.* 33 (February 1993): 3–56.
Fama, Eugene F., and Schwert, G. William. "Asset Returns and Inflation." *J. Financial Econ.* 5 (November 1977): 115–46. (*a*)
———. "Human Capital and Capital Market Equilibrium." *J. Financial Econ.* 4 (January 1977): 95–125. (*b*)
Ferson, Wayne E., and Harvey, Campbell R. "The Variation of Economic Risk Premiums." *J.P.E.* 99 (April 1991): 385–415.
Friend, Irwin, and Blume, Marshall E. "The Demand for Risky Assets." *A.E.R.* 65 (December 1975): 900–922.
Giovannini, Alberto, and Weil, Philippe. "Risk Aversion and Intertemporal Substitution in the Capital Asset Pricing Model." Working Paper no. 2824. Cambridge, Mass.: NBER, January 1989.
Grossman, Sanford J., and Shiller, Robert J. "The Determinants of the Variability of Stock Market Prices." *A.E.R. Papers and Proc.* 71 (May 1981): 222–27.
Hall, Alastair. "Some Aspects of Generalized Method of Moments Estimation." In *Econometrics,* edited by G. S. Maddala, C. R. Rao, and H. D. Vinod. Handbook of Statistics, vol. 11. Amsterdam: North-Holland, 1993.
Hall, Robert E. "Intertemporal Substitution in Consumption." *J.P.E.* 96 (April 1988): 339–57.

Hansen, Lars Peter. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* 50 (July 1982): 1029–54.

Hansen, Lars Peter, and Singleton, Kenneth J. "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns." *J.P.E.* 91 (April 1983): 249–65.

Hardouvelis, Gikas A.; Kim, Dongcheol; and Wizman, Thierry A. "Intertemporal Asset Pricing Models and the Cross Section of Expected Stock Returns." Manuscript. New Brunswick, N.J.: Rutgers Univ., Dept. Econ., 1992.

Hodrick, Robert J. "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement." *Rev. Financial Studies* 5, no. 3 (1992): 357–86.

Jagannathan, Ravi, and Wang, Zhenyu. "Conditional CAPM Is Alive and Well." Manuscript. Minneapolis: Univ. Minnesota, 1994.

Kandel, Shmuel, and Stambaugh, Robert F. "Asset Returns and Intertemporal Preferences." *J. Monetary Econ.* 27 (February 1991): 39–71.

Keim, Donald B., and Stambaugh, Robert F. "Predicting Returns in the Stock and Bond Markets." *J. Financial Econ.* 17 (December 1986): 357–90.

Li, Yuming. "Intertemporal Asset Pricing without Consumption: Empirical Tests." Manuscript. Chicago: Univ. Chicago, Grad. School Bus., 1991.

Lintner, John. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Rev. Econ. and Statis.* 47 (February 1965): 13–37.

Lo, Andrew W., and MacKinlay, A. Craig. "Data-Snooping Biases in Tests of Financial Asset Pricing Models." *Rev. Financial Studies* 3, no. 3 (1990): 431–67.

MacKinlay, A. Craig. "Multifactor Models Do Not Explain Deviations from the CAPM." *J. Financial Econ.* 38 (May 1995): 3–28.

Mankiw, N. Gregory, and Shapiro, Matthew D. "Risk and Return: Consumption Beta versus Market Beta." *Rev. Econ. and Statis.* 68 (August 1986): 452–59.

Mayers, David. "Nonmarketable Assets and Capital Market Equilibrium under Uncertainty." In *Studies in the Theory of Capital Markets,* edited by Michael C. Jensen. New York: Praeger, 1972.

Mehra, Rajnish, and Prescott, Edward C. "The Equity Premium: A Puzzle." *J. Monetary Econ.* 15 (March 1985): 145–61.

Merton, Robert C. "An Intertemporal Capital Asset Pricing Model." *Econometrica* 41 (September 1973): 867–87.

Nieuwland, Frederick G. M. C. "Intertemporal Asset Pricing without Consumption: A GARCH Approach." Manuscript. Maastricht, Netherlands: Univ. Limburg, Dept. Econ., 1991.

Ogaki, Masao. "Generalized Method of Moments: Econometric Applications." In *Econometrics,* edited by G. S. Maddala, C. R. Rao, and H. D. Vinod. Handbook of Statistics, vol. 11. Amsterdam: North-Holland, 1993.

Poterba, James M., and Summers, Lawrence H. "Mean Reversion in Stock Prices: Evidence and Implications." *J. Financial Econ.* 22 (October 1988): 27–59.

Restoy, Fernando. "Optimal Portfolio Policies under Time-Dependent Returns." Manuscript. Madrid: Bank of Spain, 1992.

Roll, Richard R. "A Critique of the Asset Pricing Theory's Tests: Part I: On Past and Potential Testability of the Theory." *J. Financial Econ.* 4 (March 1977): 129–76.

Roll, Richard R., and Ross, Stephen A. "An Empirical Investigation of the Arbitrage Pricing Theory." *J. Finance* 35 (December 1980): 1073–1103.

Romer, Christina D. "The Prewar Business Cycle Reconsidered: New Estimates of Gross National Product, 1869–1908." *J.P.E.* 97 (February 1989): 1–37.

Ross, Stephen A. "The Arbitrage Theory of Capital Asset Pricing." *J. Econ. Theory* 13 (December 1976): 341–60.

Shanken, Jay, and Weinstein, Mark I. "Macroeconomic Variables and Asset Pricing: Estimation and Tests." Manuscript. Rochester, N.Y.: Univ. Rochester, 1990.

Sharpe, William. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *J. Finance* 19 (September 1964): 425–42.

Shiller, Robert J. "Aggregate Income Risks and Hedging Mechanisms." Working Paper no. 4396. Cambridge, Mass.: NBER, July 1993.

Siegel, Jeremy J. "The Real Rate of Interest from 1800–1990: A Study of the U.S. and the U.K." *J. Monetary Econ.* 29 (April 1992): 227–52.

Sims, Christopher A. "Macroeconomics and Reality." *Econometrica* 48 (January 1980): 1–48.

Stambaugh, Robert F. "On the Exclusion of Assets from Tests of the Two-Parameter Model: A Sensitivity Analysis." *J. Financial Econ.* 10 (November 1982): 237–68.

Stock, James H., and Watson, Mark W. "New Indexes of Coincident and Leading Economic Indicators." In *NBER Macroeconomics Annual 1989,* edited by Olivier J. Blanchard and Stanley Fischer. Cambridge, Mass.: MIT Press, 1989.

———. "Business Cycle Properties of Selected U.S. Economic Time Series, 1959–88." Working Paper no. 3376. Cambridge, Mass.: NBER, June 1990.

Summers, Lawrence H. "Tax Policy, the Rate of Return, and Savings." Working Paper no. 995. Cambridge, Mass.: NBER, September 1982.

Weil, Philippe. "The Equity Premium Puzzle and the Risk-Free Rate Puzzle." *J. Monetary Econ.* 24 (November 1989): 401–21.