The Variation of Economic Risk Premiums

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This paper provides an analysis of the predictable components of monthly common stock and bond portfolio returns. Most of the predictability is associated with sensitivity to economic variables in a rational asset pricing model with multiple betas. The stock market risk premium is the most important for capturing predictable variation of the stock portfolios, while premiums associated with interest rate risks capture predictability of the bond returns. Time variation in the premium for beta risk is more important than changes in the betas.

I. Introduction

It is well documented that the rates of return to holding common stocks and bonds are to some extent predictable over time. There is controversy over the source of the predictability. Some authors attribute predictability to market inefficiencies, and others maintain that predictability is the result of changes in the required return. In this

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paper we attempt to calibrate the relative importance of these two explanations for monthly portfolio returns. Our evidence suggests that a rational asset pricing model that focuses on risk can explain most of the predictability.

The asset pricing models imply that the expected returns of securities are related to their sensitivity to changes in the state of the economy. Sensitivity is measured by the securities' "beta" coefficients. For each of the relevant state variables, there is a marketwide price of beta measured in the form of an increment to the expected return (a "risk premium") per unit of beta. In such a model, the predictable variation of returns can be driven by changes in the betas and changes in the price of beta. Previous studies have identified state variables that are "priced," in the sense that the risk premiums are different from zero on average. Much research has examined the time-series behavior of betas, but the time-series behavior of the risk premiums has received relatively little attention.

This paper studies the behavior of economic risk premiums over time. We use proxies for the state variables that are representative of earlier studies. A cross-sectional regression approach is used to decompose the predictable part of the portfolio returns to examine the portion "explained" by the model and to assess the relative importance of time-varying risk and time-varying risk premiums. We also decompose the variance of predicted returns to assess the relative importance of the economic risk variables. We find that the premium associated with stock market risk is the most important for purposes of capturing predictable variation of the common stock portfolios, while premiums associated with interest rate risks capture predictability of the bond portfolio returns. We also find that time variation in the expected risk premiums—not the betas—is the primary source of predictability at the portfolio level.

The paper is organized as follows. Section II describes the methodology. Section III describes the data. The behavior of risk premiums associated with the economic risk variables is examined in Section IV. Section V summarizes our conclusions.

II. Methodology

We study models that attribute predictability of returns to changes in the expected compensation for risk. The simplest example is a conditional version of the capital asset pricing model (CAPM) (see Sharpe 1964; Merton 1973; Constantinides 1980):

$$E(R_{it}|\mathbf{Z}_{t-1}) = \gamma_0(\mathbf{Z}_{t-1}) + b_{im,t-1}\gamma_m(\mathbf{Z}_{t-1}), \tag{1}$$

where R_{it} is the rate of return of asset i between times $t-1$ and t; $b_{im,t-1}$ is the market beta (the beta is the ratio of the conditional covariance of the return with the market portfolio divided by the conditional variance of the market portfolio); $\mathbf{Z}_{t-1}$ is the conditioning information, assumed to be publicly available at time $t - 1$; $\gamma_m(\mathbf{Z}_{t-1})$ is the price of the market beta; and $\gamma_0(\mathbf{Z}_{t-1})$ is the expected return of all portfolios with market beta equal to zero. If there is a risk-free asset available at time $t - 1$, then its rate of return equals $\gamma_0(\mathbf{Z}_{t-1})$.

Rational expectations implies that the actual return differs from the conditional expected value by an error term, u_{it}, which is orthogonal to the information at time $t - 1$. Therefore, if the actual returns are predictable using information in $\mathbf{Z}_{t-1}$, the model implies that either the betas or the premiums, $\gamma_m(\mathbf{Z}_{t-1})$ and $\gamma_0(\mathbf{Z}_{t-1})$, are changing as functions of $\mathbf{Z}_{t-1}$.

A. *The Cross-sectional Regression Approach*

Cross-sectional regression methods similar to those used by Fama and MacBeth (1973) can be used to study the predictability of returns. The standard approach is a two-step procedure. In the first step, instruments for the betas are obtained using time-series methods (discussed below). The second step is to estimate a cross-sectional regression, for each month t, of the ex post asset returns on the ex ante betas. We conduct our analysis using *excess returns* $r_{it} = R_{it} - R_{ft}$, where R_{ft} is the return of a 1-month Treasury bill. Since our focus is the predictability of returns and the Treasury bill return is known at the beginning of the month, it makes sense to study the excess returns. We do not assume that the real return of the bill is risk-free.[1]

The cross-sectional regression equation for month t is

$$r_{it} = \lambda_{0t} + \lambda_{mt}\beta_{im,t-1} + e_{it}, \quad i = 1, \ldots, N, \tag{2}$$

where λ_{0t} is the intercept, λ_{mt} is the slope coefficient, and $\beta_{im,t-1}$ is the instrument for the conditional beta of the excess return for asset i in month t ($\beta_{im,t-1} = b_{im,t-1} - b_{fm,t-1}$, and $b_{fm,t-1}$ is the beta of the Treasury bill). The dating convention indicates that the conditional beta is formed using only information available at time $t - 1$.

The regression equation provides a decomposition of each excess return each month into two components: The first component, $\lambda_{mt}\beta_{im,t-1}$, represents the part of the return of asset i that is related to the cross-sectional structure of risk, as measured by the betas. The remaining component of the return is the sum of the residual for the asset and the intercept for month t, $e_{it} + \lambda_{0t}$. This is the part of the return that is uncorrelated with the measures of risk. The asset pricing model implies that the predictability of returns should be

[1] Since the excess nominal returns approximate the excess real returns, this approach has the additional advantage of avoiding the specification of a price deflator.

due to the component that is related to risk. The part of the return that is unrelated to risk should be unpredictable.[2]

B. *Generalizing to Multiple Betas*

The approach described above generalizes easily to models with multiple betas. Such models are derived from the analysis of optimal portfolio choices through time. An Euler equation implies that expected returns are related, at each date, to the conditional covariances of returns with a measure of marginal utility. Given a linear, multivariate proxy for marginal utility using a number of state variables, a multiple-beta model describes expected returns.[3] A multiple-beta model asserts the existence of expected premiums $\gamma_j(\mathbf{Z}_{t-1}), j = 0, \ldots, K$, such that expected returns, conditional on the information $\mathbf{Z}_{t-1}$, can be written as

$$E(R_{it}|\mathbf{Z}_{t-1}) = \gamma_0(\mathbf{Z}_{t-1}) + \sum_{j=1}^{K} b_{ij,t-1}\gamma_j(\mathbf{Z}_{t-1}). \tag{3}$$

The $b_{ij,t-1}$ are the conditional betas (multiple regression coefficients) of the R_{it} on K state variables, $j = 1, \ldots, K$. We shall specify proxies for the state variables.[4]

The cross-sectional regression for the multiple-beta model is

$$r_{it} = \lambda_{0t} + \sum_{j=1}^{K} \lambda_{jt}\beta_{ij,t-1} + e_{it}, \quad i = 1, \ldots, N, \tag{4}$$

where $\beta_{ij,t-1} = b_{ij,t-1} - b_{fj,t-1}$ are the conditional betas of the excess returns. A slope coefficient in this regression, $\lambda_{jt}, j = 1, \ldots, K$, is a "mimicking portfolio" return whose conditional expected value is an estimate of the risk premium, or price of beta, $\gamma_j(\mathbf{Z}_{t-1})$, for economic variable j. An economic variable is priced if the expected value of its premium is different from zero. This implies that expected returns differ across the assets, depending on their betas with respect to the economic variable.

[2] The expected value of the slope coefficient is an estimate of the expected market premium, $\gamma_m(\mathbf{Z}_{t-1})$. The CAPM implies that the population intercept term should be equal to zero.

[3] See, e.g., Sharpe (1977), Cragg and Malkiel (1982), or Shanken (1987). Examples of such models also include Merton (1973), Long (1974), Ross (1976), and Breeden (1979).

[4] When the proxies are portfolio returns constructed from the sample of assets, then eq. (3) is equivalent to the statement that a combination of these portfolios is mean-variance efficient. See Breeden (1979), Grinblatt and Titman (1987), and Huberman, Kandel, and Stambaugh (1987) for discussions and refinements.

The cross-sectional regression provides a decomposition of each excess return for each month. The first component, $\Sigma_{j=1}^{K} \lambda_{jt}\beta_{ij,t-1}$, is the part of the return of asset i that is related to the measures of risk. The remaining component for month t, $\lambda_{0t} + e_{it}$, is the part of the asset return that is uncorrelated with the measures of risk.

C. *Econometric Issues*

Any inference about market efficiency involves a joint hypothesis (Fama 1970). If the model is misspecified, then predictable variation in the misspecification can contaminate the $\lambda_{0t} + e_{it}$ component.[5] It is conceivable that inefficiencies are systematically related across assets to differences in the betas and are predictable by means of predetermined variables. Such inefficiencies could masquerade as priced state variables in the multibeta model. Our approach of decomposing monthly returns may have low power to detect some kinds of predictable patterns of the model errors captured in $\lambda_{0t} + e_{it}$.[6] However, if most of the predictability of returns is explained within the model, the appeal of the rational asset pricing paradigm is strengthened.

The cross-sectional regression requires instruments for the betas, $\beta_{ij,t-1}$. The most common approach is to regress the excess returns on the economic variables using the time series for months $t - 60$ to $t - 1$. The slope coefficients in the time-series regressions provide estimates of the betas. We use these coefficients as instruments for the *conditional* betas, given information available at month $t - 1$. Of course, such "rolling regressions" may not produce the best estimates of conditional betas. In an appendix (available, by request, from the authors), we examine the sensitivity of our results to the way in which the betas are estimated. The main results presented here are robust.[7]

Even if the "true" betas are known, the second-step, cross-sectional regressions are complicated because the returns are correlated and

[5] For example, if there is an omitted state variable with similar betas for most of the assets but a different beta for the Treasury bill, then the risk premium for that factor will enter via the λ_{0t} term.

[6] For example, speculative bubbles or slow-moving, mean-reverting shocks may be hard to detect this way (see Lo and MacKinlay 1988). See Durlauf and Hall (1989) for an analysis of the bounds on model errors in expectation models of stock prices.

[7] We examine five kinds of beta estimates, which are chosen to capture a range of potential time variation in the betas: (1) the smoothest, which are held nearly constant over the sample period at the values given by ordinary least squares (OLS) slope coefficients; (2) conditional beta coefficients in which the regressions include the vector of predetermined variables, $\mathbf{Z}_{t-1}$, described earlier; (3) the 5-year rolling OLS regression betas; (4) a 60-month rolling beta estimator in which the regressors include the six economic variables and $\mathbf{Z}_{t-1}$; and (5) highly variable conditional beta estimates formed using an extension of the methods of Davidian and Carroll (1987). The Davidian and Carroll betas are described in detail in our appendix.

heteroskedastic. Conclusions based on the usual standard errors for these regressions are unreliable. Since the betas are estimated with error, the regressions involve errors in the variables. A "t-ratio" for testing the hypothesis that the average premium is zero is calculated using the standard deviation of the time series of estimated risk premiums, as in Fama and MacBeth (1973). Such t-ratios are unbiased in large samples under the null hypothesis that the mean premiums are zero. In small samples, given the possibility of correlated measurement errors in the betas and observations that may not be independent over time, even the Fama-MacBeth t-ratios should be interpreted with caution.[8] We report results for OLS cross-sectional regressions. We also examine weighted least squares regressions, in which we deflate each cross-sectional observation for month t by the standard deviation of the residual from the time-series regression that is used to estimate the beta of the asset for month t.[9] In addition, we calculate alternative t-ratios using a correction for errors in the betas suggested by Shanken (1989).[10]

Errors in the variables could affect our inferences when the fitted premiums are used as dependent variables in time-series regressions to assess predictability. A pure attenuation bias, which shrinks the cross-sectional regression coefficients toward zero, would create a tendency to understate the predictable variation captured by the model. If the biases are correlated with the predetermined information variables, the error could work in either direction. Even if the premium estimates were unbiased, estimation error in the premiums would distort the standard errors.[11]

We conduct two kinds of experiments to assess the sensitivity of our results to errors in variables. First, we repeat the analyses of predictability using five alternative beta estimators, chosen to represent a range of variability and susceptibility to errors in variables. Second, we replicate the analyses using a coefficient estimator adjusted for errors-in-variables bias. These experiments show that the main results are robust.

Finally, we conduct bootstrap experiments to assess the small-sample properties of the statistics that we use to test the hypothesis

[8] See Shanken (1989) for a review and analysis of the large-sample issues. See Amsler and Schmidt (1985) for evidence on the small-sample properties of the cross-sectional regression estimators.

[9] Chan, Chen, and Hsieh (1985) adopt a similar approach. Shanken (1989) provides conditions under which a generalized least squares, two-stage estimator is consistent and asymptotically efficient.

[10] This correction accounts for autocorrelation in the economic variables. The results are in an appendix that is available from the authors.

[11] See Pagan (1984, 1986) for general analyses of consistency and asymptotic efficiency in models with generated regressors.

TABLE 1

INDUSTRY PORTFOLIO GROUPS

Portfolio Number	Two-Digit SIC Codes	Industry Name
1	13, 29	Petroleum
2	60–69	Finance/real estate
3	25, 30, 36–37, 50, 55, 57	Consumer durables
4	10, 12, 14, 24, 26, 28, 33	Basic industries
5	1, 20, 21, 54	Food/tobacco
6	15–17, 32, 52	Construction
7	34–35, 38	Capital goods
8	40–42, 44, 45, 47	Transportation
9	46, 48, 49	Utilities
10	22–23, 31, 51, 53, 56, 59	Textiles/trade
11	72–73, 75, 80, 82, 89	Services
12	27, 58, 70, 78–79	Leisure

that the model can capture the predictable variation of asset returns. These experiments are described below.

III. The Data

We study monthly common stock and bond returns. The stocks are of firms listed on the New York Stock Exchange (NYSE). The bonds are a long-term government bond, a long-term corporate bond, and the Treasury bill that is the closest to 6 months to maturity. The data are provided by the Center for Research in Security Prices (CRSP) at the University of Chicago. Ten common stock portfolios are formed according to size deciles on the basis of the market value of equity outstanding at the beginning of each year. The 10 "size" portfolios are value-weighted averages of the firms. (Value weighting approximates a "buy-and-hold" investment strategy.) We also include 12 portfolios of NYSE firms grouped by two-digit standard industrial classification (SIC). In contrast to the size portfolios, the number of firms in each industry portfolio is not approximately the same.[12] We include a firm in the portfolio for its industry in every month for which a return, a price per common share, and the number of shares outstanding are recorded by CRSP. The portfolios are value weighted each month. Table 1 presents the SIC codes of the industry groups.

[12] The industry classification follows Sharpe (1982), Breeden, Gibbons, and Litzenberger (1989), and others. The number of firms in a portfolio varies from a low of eight (services industry before September 1960) to a high of 300 (finance/real estate in October 1986). The mean number of firms over the 1959–86 sample period varies across the industries from 33.6 (services) to 213.7 (basic industries).

TABLE 2

Economic Variables

Symbol	Definition	Source
XVW	Value-weighted NYSE index return less 1-month Treasury bill return	CRSP
CGNON	Monthly real per capita growth of personal consumption expenditures for nondurable goods, seasonally adjusted	Commerce Department
PREM	Monthly return of corporate bonds rated Baa by Moody's Investor Services less the long-term U.S. government bond return (CRSP)	Ibbotson corporate bond module
ΔSLOPE	Change in the difference between the average monthly yield of a 10-year Treasury bond and a 3-month Treasury bill	*Federal Reserve Bulletin*
UI	Unexpected inflation rate: the difference between the actual and the forecasted inflation rate, formed from a time-series model for percentage changes in the CPI for all urban consumers, not seasonally adjusted	CRSP
REALTB	1-month Treasury bill return less the monthly rate of inflation, as measured by the CPI	CRSP

A. *Economic Risk Variables*

We study a number of proxies for the economic risks that influence security returns. Table 2 lists the variables. The list is representative of earlier studies that found that the average price of beta for such variables was nonzero (see Fogler, John, and Tipton 1981; Chan et al. 1985; Chen, Roll, and Ross 1986; Sweeney and Warga 1986; Shanken and Weinstein 1987; McElroy and Burmeister 1988). Of course, there is no claim that the variables uniquely capture the relevant economic risks. They could jointly proxy for a set of latent variables that determine security returns. But the specific variables are of some economic interest.

Theory provides some motivation for the state variable proxies. The CAPM indicates a role for the "market portfolio" of aggregate wealth, and studies of the CAPM typically use a proxy from the stock market. The variable XVW is the return of the CRSP value-weighted stock market index in excess of a 1-month Treasury bill return.

There is a long tradition in economics of using an interest rate to capture the state of investment opportunities. Merton (1973) and Cox, Ingersoll, and Ross (1985) develop models in which interest rates are state variables. The variable REALTB is the real 1-month

Treasury bill return, measured as the nominal rate less the rate of change in the consumer price index.

The asset pricing models of Merton (1973), Lucas (1978), and Breeden (1979) imply that "priced" state variables must covary with the aggregate marginal utility of wealth. Marginal utility should vary inversely with changes in aggregate consumption when markets are complete and perfect and utility is time and state separable. Breeden et al. (1989) found that consumption betas are useful in describing a cross-section of average returns. The variable CGNON is the real per capita growth rate of personal consumption expenditures for nondurable goods.

Unanticipated inflation could be a source of economic risk if inflation has real effects, in the sense that inflation is correlated with aggregate marginal utility. If firms also differ in their exposure to changes in inflation, there may be an inflation risk premium in the multiple-beta model. The variable UI is the unexpected inflation rate, measured as the residual from a time-series model for the percentage changes in the consumer price index.[13]

The variable PREM is the difference between the monthly returns of corporate bonds rated Baa by Moody's Investor Services and the return of a long-term U.S. government bond.[14] Chan et al. (1985) and Chen et al. (1986) propose such a state variable as a measure of changes in the risk of corporate default.[15]

The variable ΔSLOPE is the change in the difference between the average yield to maturity of a 10-year Treasury bond and a 3-month Treasury bill. This variable attempts to capture risk as reflected in the changing slope of the Treasury yield curve.

[13] We use an IMA(1, 1) model for the inflation rate:

$$I_t = 2.1\text{E-}06 + I_{t-1} + a_t - .724a_{t-1}; \quad \text{adj. } R^2 = .54,$$

where I_t is the inflation rate and a_t is a white-noise error term. Fama and Gibbons (1984) applied time-series models to the real returns of Treasury bills and subtracted the fitted expected real return from the nominal bill rate to obtain a measure of expected inflation. We estimated such a model. Standard Box-Jenkins analysis suggested an IMA(1, 1) with a moving average parameter equal to .93 (standard error .03) for the real return. We found little difference between these two models in the accuracy of the inflation forecasts over our sample period.

[14] We thank Roger Ibbotson for making the low-grade corporate bond return data available.

[15] We examined several definitions of the PREM variable. These included the change in the average monthly yield difference between Baa bonds and Aaa bonds, the difference in the rates of return for these two bond categories, and the difference between the Baa and the composite corporate bond returns. We found that the results on the average pricing of PREM were highly sensitive to the definition of the variable and the subperiod. We decided to retain the definition of PREM employed by Chan et al. (1985) for our analysis.

TABLE 3

INSTRUMENTS

Symbol	Definition	Source
XEW(− 1)	Equal-weighted NYSE index return less 1-month Treasury bill return	CRSP
HB3(− 1)	1-month return of a 3-month Treasury bill less the 1-month return of a 1-month bill	CRSP
JUNK(− 1)	Average monthly yield to maturity of corporate bonds rated Baa by Moody's Investor Services less the Aaa corporate bond yield	*Federal Reserve Bulletin*
DIV(− 1)	Monthly dividend yield on the Standard and Poor's 500 stock index	*Federal Reserve Bulletin*
TB1	Nominal 1-month Treasury bill rate	CRSP

B. *Information Variables*

Ideally, we would like to measure the information that investors use to set prices in the market. We use instrumental variables. Table 3 summarizes the variables.

The variable XEW(− 1) is the lagged return of the equal-weighted NYSE index from CRSP, in excess of the 1-month Treasury bill rate. The − 1 indicates that the variable is lagged 1 month. A lagged index return follows Conrad and Kaul (1988), Fama and French (1988*b*), and others.

The variable HB3(− 1) is the 1-month return of a 3-month Treasury bill less the 1-month return of a 1-month bill. Campbell (1987) finds that such measures of the short-maturity term structure can predict monthly returns in both the bond and the stock markets.

The variable DIV(− 1) is the sum of the previous year's dividends on the Standard and Poor's 500 stock index divided by the price level in a given month. Using annual dividend payments removes the seasonality of dividends. Dividend yields are a component of the return of stocks, so the dividend yield is a natural instrument for capturing predictability of stock returns. Campbell and Shiller (1988), Fama and French (1988*a*, 1989), and others examine similar variables. The dividend variable is correlated with the inverse of the price level of common stocks, a variable studied by Keim and Stambaugh (1986). Such variables may capture potential mean reversion in the stock market. Mean reversion suggests that if stock returns are below average (so that prices are relatively low and yields are high), then expected returns may be higher than average.

The variable JUNK(− 1) is the monthly average yield to maturity of corporate bonds rated Baa by Moody's Investor Services less the Aaa corporate bond yield. Keim and Stambaugh (1986) find that a yield spread has some predictive power for future bond and stock returns.

The variable TB1 is the nominal 1-month Treasury bill rate. The ability of short-term bills to predict monthly returns of bonds and stocks is documented by Fama and Schwert (1977), Ferson (1989), and others.[16]

The predetermined variables follow empirical work that uses portfolios similar to the ones we study. There is a natural concern about predictability uncovered through collective "data snooping" by a series of researchers. Such a bias is conservative for our purposes because spurious predictability of the returns should be difficult to "explain" using an economic model. Some corroboration for the predictability is available from studies using international data,[17] and some theoretical support for the predictability is also available. Grossman (1981) argued that the parameters of the CAPM should be conditional on the prices of assets. Bossaerts and Green (1989) developed a model in which conditional expected returns are inversely related to the price of an asset. Kandel and Stambaugh (1989) developed a model economy in which a dividend yield, a default-related yield spread, and a measure of the term structure slope track time-varying expected risk premiums.

C. *Summary Statistics*

Table 4 presents summary statistics for the returns, measured in excess of the 1-month Treasury bill rate, and for the economic risk variables and the predetermined information variables. Summary statistics for the size portfolios and the bonds are familiar from previous studies. The services industry portfolio, which has the smallest number of firms, also has the largest standard deviation of the industry portfolios. The utilities industry has the lowest standard deviation. There is typically only mild first-order autocorrelation of the returns (on the order of 0.1–0.2), but the autocorrelations of some of the instruments are significantly higher.[18]

[16] We use the 1-month bill rate from the CRSP-Fama files as an instrument and compute excess returns relative to the 1-month rate from Ibbotson Associates to minimize measurement error problems. The CRSP-Fama files use the Treasury bill that is the closest to 1 month to maturity, while the Ibbotson rates pertain to a bill with at least 1 month to maturity.

[17] Cutler, Poterba, and Summers (1988) found that dividend yields had predictive power for future stock returns in many countries. Campbell and Hamao (1989) found that predictable components of bond and stock returns were highly correlated between the United States and Japan.

[18] Some of the first-order autocorrelations of the instruments are above 0.9 (i.e., JUNK, DIV, and TB1). This is expected for DIV because the numerator is an annual figure sampled monthly and is therefore overlapping. The autocorrelations of all the series decay toward zero at long lags.

TABLE 4

SUMMARY STATISTICS FOR THE ASSET EXCESS RETURNS, ECONOMIC VARIABLES, AND INSTRUMENTAL VARIABLES (in Percentages per Month) FOR 1959:5–1986:12 (332 Observations)

Portfolio	Mean	Standard Deviation
	Asset Excess Returns	
Decile:		
1	.95	7.21
2	.89	6.30
3	.80	6.05
4	.78	5.64
5	.65	5.41
6	.61	5.16
7	.58	5.09
8	.54	4.85
9	.45	4.59
10	.28	4.07
Industry:		
Petroleum	.51	5.20
Finance/real estate	.45	4.74
Consumer durables	.37	5.25
Basic industries	.27	4.64
Food/tobacco	.59	4.29
Construction	.24	5.62
Capital goods	.39	5.10
Transportation	.37	6.01
Utilities	.36	3.66
Textiles/trade	.52	5.45
Services	.52	6.32
Leisure	.65	6.30
Government bonds	.03	2.90
Corporate bonds	.06	2.70
6-month Treasury bill	.08	.28
	Economic Variables	
XVW	.36	4.26
PREM	.06	2.15
ΔSLOPE	.00	.04
UI	.00	.24
CGNON	.11	.78
REALTB	.10	.30
	Instrumental Variables	
XEW	.64	5.32
HB3	.05	.12
JUNK	.09	.04
DIV	.32	.08
TB1	.49	.24

NOTE.—All rates of return are in excess of the 1-month Treasury bill rate. Decile 1 represents the excess returns on the decile of smallest-valued firms on the NYSE. Decile 10 represents the excess returns on the largest decile of NYSE stocks. Economic and instrumental variables are defined in tables 2 and 3.

We estimate the predictable part of the returns by regressing them on the predetermined variables. The signs and magnitudes of the regression coefficients are not surprising, given earlier studies.[19] The adjusted R^2's exceed 4 percent for each of the 25 portfolio returns, and 16 of the 25 exceed 10 percent.[20] Thus the predetermined variables uncover some predictability of excess returns in both the bond and stock markets. The predictable components have time-series properties like those of the instruments. To the extent that the predictability reflects time-varying expected returns, the expected returns are modeled as highly autocorrelated time series. The low autocorrelations of the actual returns then reflect the large unpredictable component in monthly returns.

The contemporaneous correlations of the variables suggest that none is redundant, and multicollinearity should not be a problem. The largest correlations among the economic variables occur between REALTB and UI ($-.698$) and between UI and XVW ($-.218$). Only three of the contemporaneous correlations among the instruments exceed .5, and the largest is .74.

IV. Empirical Results

Table 5 reports the average, over time, of the risk premium estimates associated with the economic variables. A *t*-ratio (in parentheses) is reported for the hypothesis that a mean premium is equal to zero. These are calculated as in Fama and MacBeth (1973). The first panel summarizes results for bivariate asset pricing models, where the value-weighted stock index is the first state variable. The premiums pertain to the "nonmarket" risk associated with the economic variables. When only the bond returns and the 10 size-ranked stock portfolios are used, the average premiums for market risk, default risk, and real interest rate risk are positive. The average premium for unexpected inflation is negative. The magnitudes of the average premiums are similar to those of previous studies. But the premium for the PREM variable is smaller than that reported by Chan et al. (1985) and Chen et al. (1986).[21] The *t*-statistics recorded for XVW and

[19] The variable DIV(-1) enters with a positive coefficient in each of the regressions. Its coefficient is several standard errors from zero in the stock return regressions but is smaller for the bond returns. The variable JUNK(-1) has a strong, positive relation with most of the returns. The variable TB1 enters with negative coefficients.

[20] These figures refer to regressions that include a dummy variable for the month of January. When we do not include a January dummy, the adjusted R^2's range from 3.8 percent to 13.2 percent, and 15 of the 25 are larger than 10 percent.

[21] These studies use 20 equally weighted size-based stock portfolios, slightly different data for the PREM variable, and a different sample period. Shanken and Weinstein (1987) find that a different variation on the methodology weakens the evidence for

TABLE 5

AVERAGE RISK PREMIUMS ASSOCIATED WITH ECONOMIC VARIABLES (in Percentages per Month) FOR 1964:5–1986:12 (272 Observations)

	VARIABLE					
	XVW	PREM	ΔSLOPE	UI	CGNON	REALTB
			Bivariate Models			
Size and bond portfolios	.693* (2.23)	.422 (1.80)	.026 (1.92)	−.130 (−1.71)	.135 (.53)	.175 (2.42)
Industry, size, and bond portfolios	.471* (1.61)	.447 (2.01)	.018 (2.57)	−.089 (−1.81)	.319 (2.11)	.103 (2.16)
			Multivariate Model			
Industry, size, and bond portfolios	.272 (1.07)	.378 (1.94)	.020 (2.47)	−.043 (−.93)	.328 (2.14)	.040 (.84)

NOTE.—The variables are defined in table 2. The model is

$$r_{it} = \lambda_{0t} + \sum_{j=1}^{6} \lambda_{jt}\beta_{ij,t-1} + \epsilon_{it},$$

where β_{ij} is the ith asset's sensitivity to the jth economic variable; $\beta_{ij,t-1}$ is estimated as the slope coefficient in a time-series regression using data for months $t - 60$ to $t - 1$. Cross-sectional OLS regressions for each month t produce the risk premium estimates λ_{jt}. The t-statistics for the average of the risk premiums over time are in parentheses. They are calculated from the time series of the estimates of λ_{jt}.

* This cross-sectional model is estimated with two risk measures: the value-weighted market return and one other economic variable. The betas are multiple regression betas. The statistics for XVW come from a cross-sectional model estimated with only one risk measure.

REALTB in the bivariate models are greater than 2.0. The t-ratios for PREM (1.80) and ΔSLOPE (1.92) are close to two.

In the combined sample of size, industry, and bond portfolios, the average risk premiums have the same signs and similar magnitudes, as in the size and bond portfolio subsample. One notable difference is that the t-statistic of the growth of nondurables consumption rises to 2.1 when the industry portfolios are included.

The bottom panel of table 5 summarizes a multivariate model using all six economic variables. The t-statistics recorded for PREM, ΔSLOPE, and CGNON are near 2.0, and the signs of the mean premium estimates are unchanged.[22] Consistent with Chen et al. (1986), the mean premium for the stock market index and its t-statistic (1.07) are relatively small in the multivariate model. On the basis of the

pricing of the PREM variable. Weighted least squares regressions produce slightly smaller average point estimates of the λ's, except for the PREM variable, in which the point estimates are slightly larger. But the overall impressions from the two approaches are similar. Our appendix provides further evidence on the sensitivity.

[22] We compute alternative t-ratios using the standard error correction suggested by Shanken (1989). The correction shrinks the t-ratios toward zero. It has only a small effect on the t-ratio for XVW, but the other t-ratios shrink by about 10–20 percent after this adjustment. (These are reported in our appendix.)

small average premium, Chen et al. argue that other economic variables largely subsume the market premium.

A. *Predictable Variation in Risk Premiums*

Table 6 summarizes time-series regressions of the fitted premiums on the predetermined information variables.[23] Although the average premium for the stock market index is not significant in the multiple-beta model, the adjusted R^2 in the predictive regression is near 10 percent. This suggests that the expected compensation for stock market risk is larger at some times and smaller at other times, depending on economic conditions as tracked by the predetermined variables. It could be a mistake to omit the market index from a model on the basis of a small average premium.

The stock market premiums in the multivariate model (second panel) and the bivariate model (first panel) produce similar regression coefficients. The premium is positively related to the dividend yield and negatively related to the short-term bill rate.[24] The bottom row of table 6 reports a regression for the value-weighted market proxy, XVW. The regression coefficients are similar. A regression for the sum of the premiums from the multivariate model is also reported, and again the coefficients are similar. This is consistent with the dominant role we find for the stock market premium in capturing the predictable variation of the portfolio returns.

The *t*-statistics and average premiums for both UI and REALTB are small in the multibeta model, but the adjusted R^2's indicate predictable time variation, so the expected premiums could be important at some times.[25] The expected premiums for real interest rate and consumption risks have a weak negative association with the slope of the term structure. The January dummy variable is the strongest predictor of the PREM premium, and it enters more than half of the regressions significantly.

[23] The standard errors of the coefficients are adjusted for heteroskedasticity and autocorrelation using the covariance matrix suggested by Newey and West (1987), with 11 moving average terms. The OLS standard errors were typically only slightly smaller.

[24] The estimators in the two panels are, of course, different portfolios. In the bivariate model, the coefficient is the return of a portfolio of minimum sample variance and beta on XVW equal to 1.0. In the multivariate model, the portfolio is constrained to be uncorrelated with the other state variables. See Fama (1976) and Lehmann and Modest (1988) for portfolio interpretations of cross-sectional regression estimators.

[25] Our appendix shows that these results are not highly sensitive to the way in which the betas are estimated. Similar results are obtained when the premium estimates incorporate a correction factor for errors-in-variables bias. In another experiment, we varied the "window" of the rolling beta estimates, using several windows between 4 and 10 years in length. The results of these regressions were also similar to those in table 6.

TABLE 6

Regressions of the Risk Premiums on the Instrumental Variables, 1964:5–1986:12 (272 Observations)

Premium	Instruments							
	δ_0	δ_1 (XEW)	δ_2 (JAN)	δ_3 (HB3)	δ_4 (JUNK)	δ_5 (DIV)	δ_6 (TB1)	$\overline{R}^2$ (%)
	Bivariate Models							
XVW*	−.03	.09	.03	1.81	10.39	17.62	−7.93	14.0
	(.01)	(.05)	(.01)	(2.03)	(8.03)	(5.31)	(2.02)	
PREM	.01	.04	.05	−.90	−6.62	2.56	−2.05	12.4
	(.01)	(.06)	(.01)	(1.61)	(6.83)	(4.01)	(1.71)	
ΔSLOPE	−.00	−.00	.00	.01	.23	−.06	.03	2.0
	(.00)	(.00)	(.00)	(.05)	(.15)	(.15)	(.05)	
UI	.00	.01	−.01	.66	−1.06	−1.62	.38	6.9
	(.00)	(.02)	(.00)	(.47)	(1.54)	(1.01)	(.37)	
CGNON	−.01	.02	.03	−1.41	−5.08	5.72	−.56	8.9
	(.01)	(.03)	(.01)	(1.05)	(5.88)	(2.22)	(1.12)	
REALTB	−.01	−.01	.01	−.55	1.23	2.12	−.45	9.5
	(.00)	(.01)	(.00)	(.38)	(1.52)	(1.10)	(.42)	

	Multivariate Model							
XVW	−.03	.01	.00	3.63	14.38	14.57	−6.73	9.9
	(.01)	(.04)	(.01)	(2.42)	(8.03)	(5.07)	(1.51)	
PREM	.00	.05	.04	−1.90	.90	−.42	−.44	10.5
	(.01)	(.04)	(.01)	(1.82)	(5.97)	(4.25)	(1.62)	
ΔSLOPE	.00	−.00	.00	.07	.14	−.05	−.02	.0
	(.00)	(.00)	(.00)	(.07)	(.17)	(.13)	(.04)	
UI	.00	.01	−.00	.78	−1.51	−.92	−.03	3.6
	(.00)	(.01)	(.00)	(.43)	(1.46)	(.81)	(.33)	
CGNON	−.00	.02	.02	−2.27	−.14	.09	.75	2.2
	(.01)	(.03)	(.01)	(1.26)	(5.01)	(2.64)	(1.08)	
REALTB	−.01	−.01	.01	−.93	2.63	1.08	−.01	7.4
	(.00)	(.01)	(.00)	(.41)	(1.86)	(.94)	(.34)	
Sum of premiums	−.02	.08	.06	−.61	16.40	14.35	−6.48	10.4
	(.01)	(.06)	(.02)	(3.93)	(11.24)	(7.08)	(2.84)	
Value-weighted market return	−.02	−.05	.01	4.88	17.21	14.35	−7.81	11.6
	(.01)	(.03)	(.01)	(2.98)	(7.06)	(4.32)	(1.37)	

NOTE.—The model estimated is

$$\lambda_{jt} = \delta_0 + \delta_1 XEW_{t-1} + \delta_2 JAN_t + \delta_3 HB3_{t-1} + \delta_4 JUNK_{t-1} + \delta_5 DIV_{t-1} + \delta_6 TB1_t + \epsilon_{jt},$$

where λ_{jt} represents the risk premium associated with the economic variable. Standard errors in parentheses are corrected for a moving average process of order MA(11) and conditional heteroskedasticity. $\overline{R}^2$ is the (adjusted) coefficient of determination for the regression of the fitted risk premiums on the predetermined instruments The instruments not previously defined are a constant and a dummy variable for the month of January (JAN).

* The bivariate models are estimated with two risk measures: the value-weighted market return and one other economic variable. The statistics for XVW are based on a cross-sectional model using only the stock market beta.

Figure 1 plots the time series of the fitted expected risk premium associated with the stock market index. The dashed line represents the values in January and the solid line plots the other 11 months. The vertical lines denote reference business cycles determined by the National Bureau of Economic Research (NBER). Of course, market expectations of economic conditions could differ from the ex post determination of business cycles by the NBER. But the figure suggests that the expected risk premium increases during economic contractions and peaks near business cycle troughs. Fama and French (1989) report similar patterns using various NYSE stock indexes.[26] They argue that countercyclical variation in expected returns is consistent with intertemporal asset pricing models. With decreasing relative risk aversion, high expected returns are required in recessions to induce investors away from current consumption and into risky investments.[27]

Figure 1 shows that the behavior of the fitted stock market risk premium in January roughly mirrors the behavior in the other 11 months, but at a higher level. We observe a similar pattern in most of the other premiums.[28] The observation that the behavior in January is like that of the other months does not "explain" the January effect, but it suggests that the same economic forces that may produce cyclical variation in the other months are also at work in the January premium.

B. Decomposing Predictable Variation

Table 7 provides an analysis of the predictable variance of the returns for the 25 portfolios. We regress each excess return on the instru-

[26] We examined the time series of monthly stock market premium estimates from Fama and MacBeth (1973) for 1947:1–1968:6 (reported in Fama [1976]), regressing them on a subset of the predetermined information variables. We observed similar patterns. Since the Fama and MacBeth estimates use portfolios formed on the basis of prior-period betas and cover a different sample period, this further suggests that the general patterns are robust.

[27] When we use the predetermined variables to predict the "nonmarket" premiums from the bivariate models, most of the fitted values appear to have countercyclical patterns. The premium for inflation risk appears procyclical. When we examined the fitted values of the monthly estimates of the expected "zero-beta" premium from Fama and MacBeth (1973), the plot appeared similar to that of the inflation premium. The zero-beta premium estimator is a portfolio with a market beta equal to zero. If the market and the zero-beta factor spanned the mean-variance frontier as predicted by CAPM, then the expected returns of all assets would be linear combinations of the two premiums. Assets with market betas above 1.0 (long the market index and short the zero-beta factor) would have more pronounced January seasonals and countercyclical expected premiums than the stock market index. Assets with market betas between zero and one would average the seasonal and cyclical patterns.

[28] Tinic and West (1984) observed that average stock market premiums are higher in January than in the other months. For all these plots we include dummy variables in the predictive regressions, allowing all the slope coefficients to differ in January from their values in the other 11 months.

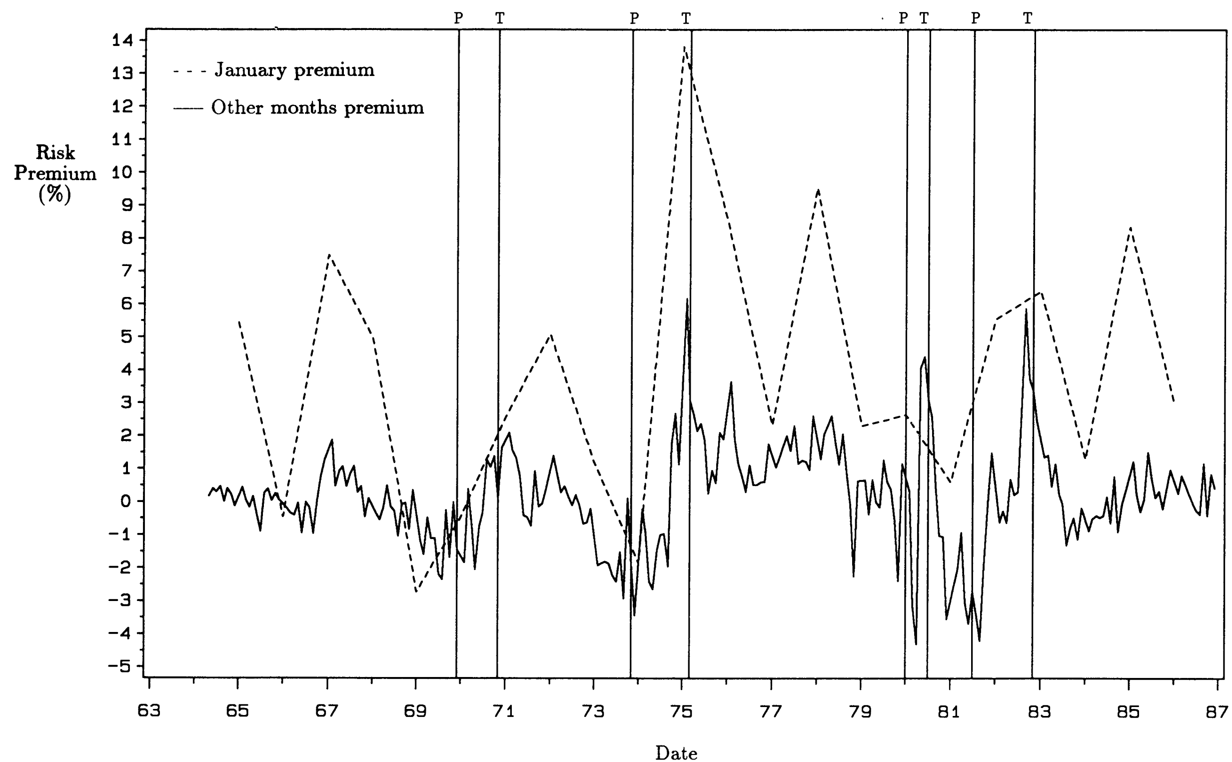

FIG. 1.—Fitted values from a regression of the price of market beta on the instrumental variables. The values for the price of market beta are the estimated coefficients from a cross-sectional regression each month of 25 portfolio returns on estimates of the market beta coefficients. The monthly estimates of the price of beta are regressed over time on the predetermined variables summarized in table 3. The regressions include dummy variables that allow each of the slope coefficients to differ in January from their values in the other months. The fitted values of the regression are shown in this graph. The dashed line represents the January observations; the solid line represents the other 11 months. The

TABLE 7

DECOMPOSITION OF THE PREDICTABLE VARIATION OF MONTHLY PORTFOLIO RETURNS, 1964:5–1986:12 (272 Observations)

Portfolio	Including January Dummy Indicator		Excluding January Dummy Indicator	
	$\frac{\mathrm{Var}[P(\hat{\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}} \mid \mathbf{Z})]}{\mathrm{Var}[P(r \mid \mathbf{Z})]}$ (VR1)	$\frac{\mathrm{Var}[P(r - \hat{\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}} \mid \mathbf{Z})]}{\mathrm{Var}[P(r \mid \mathbf{Z})]}$ (VR2)	$\frac{\mathrm{Var}[P(\hat{\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}} \mid \mathbf{Z}^0)]}{\mathrm{Var}[P(r \mid \mathbf{Z}^0)]}$ (VR1)	$\frac{\mathrm{Var}[P(r - \hat{\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}} \mid \mathbf{Z}^0)]}{\mathrm{Var}[P(r \mid \mathbf{Z}^0)]}$ (VR2)
Decile:				
1	.644 [.000]*	.071 [.009]†	.901	.016
2	.744 [.000]	.045 [.005]	.922	.014
3	.751 [.002]	.028 [.055]	.810	.021
4	.822 [.048]	.019 [.339]	.846	.019
5	.796 [.016]	.029 [.090]	.820	.029
6	.822 [.039]	.025 [.222]	.855	.022
7	.792 [.025]	.035 [.119]	.783	.037
8	.884 [.137]	.050 [.037]	.894	.051
9	.842 [.092]	.048 [.105]	.852	.046
10	.806 [.112]	.082 [.074]	.801	.078

Industry:					
Petroleum	.639	[.040]	.059	[.491]	.631	.061
Finance/real estate	.798	[.156]	.101	[.078]	.797	.091
Consumer durables	.738	[.015]	.069	[.067]	.735	.071
Basic industries	.960	[.527]	.137	[.029]	.974	.134
Food/tobacco	.810	[.182]	.121	[.081]	.819	.119
Construction	.667	[.005]	.050	[.017]	.672	.049
Capital goods	.906	[.282]	.038	[.325]	.920	.032
Transportation	.969	[.504]	.032	[.364]	.929	.032
Utilities	.559	[.028]	.305	[.052]	.609	.261
Textiles/trade	.897	[.301]	.028	[.554]	.869	.026
Services	.873	[.166]	.043	[.120]	.888	.043
Leisure	.963	[.417]	.007	[.932]	.957	.007
Government bonds	1.209	[.832]	.446	[.016]	.694	.253
Corporate bonds	.571	[.100]	.384	[.099]	.530	.331
6-month bill	.894	[.644]	.294	[.417]	.745	.208
Average	.814		.102		.810	.082

NOTE.—All rates of return are in excess of the holding period return on a 1-month Treasury bill. Decile 1 represents the excess returns on the decile of the smallest-valued firms on the NYSE. Decile 10 represents the excess returns on the largest decile of NYSE stocks. VR1 is the ratio of the variance of the model's predicted returns to the variance of expected returns from a linear regression $P(\cdot|\mathbf{Z})$ on a set of instrumental variables ($\mathbf{Z}$). VR2 is the ratio of the variance of the predictable part of a return that is not explained by the model to the variance of the expected returns. The variance ratios in the last two columns use an instrument set ($\mathbf{Z}^0$) that excludes the January dummy variable. The instrumental variables are a constant, XEW(−1), JAN, HB3(−1), JUNK(−1), DIV(−1), and TB1. The model is estimated with six economic variables: XVW, PREM, SLOPE, UI, CGNON, and REALTB.

* One-tail p-value for the test that the variance ratio equals one, based on a bootstrapped distribution with 1,000 replications.

† One-tail p-value for the test that the variance ratio equals zero, based on a bootstrapped distribution with 1,000 replications.

ments, $\mathbf{Z}_{t-1}$, and calculate the sample variance of the fitted values. The objective is to see how much of the variance is "explained" by the asset pricing model. The part captured by the model is the sample variance of the fitted values from regressing $\Sigma_{j=1}^{K} \lambda_{jt}\beta_{ij,t-1}$, from equation (4), on the instruments. We express this as a ratio, VR1, dividing by the variance of the fitted values of the excess return. The predictable component of a return that is not captured by the model is measured as the sample variance of the fitted values from regressing $\lambda_{0t} + e_{it}$ on $\mathbf{Z}_{t-1}$. This variance is also expressed as a ratio, VR2, relative to the total variance of the fitted expected return.[29]

If the model captures the predictable variation of the portfolio returns, the population ratios VR1 = 1.0 and VR2 = 0.0. If the model captures no predictable variation, the reverse is true. The hypothesis that the true ratios are VR1 = 1.0 and VR2 = 0.0 is extreme because it requires that the model capture *all* the predictable variation of returns, leaving none of it unexplained. Presumably, a model of market equilibrium can be useful even if it explains less than 100 percent of the variance.

Because of sampling variation, we expect sample values of VR1 to be less than 1.0 and VR2 to be greater than 0.0, even if the true ratios are equal to 1.0 and 0.0. Four estimation steps are involved in calculating the ratios. No theoretical small-sample properties for such statistics are available to our knowledge, so we conduct bootstrap experiments to assess them.

We calibrate the experiments by using the estimated values of the λ's and the β's as if they are the "true" parameter values. This is a conservative procedure because the additional sampling variability introduced by estimation error in these parameters, but not accounted for in our experiments, should widen the confidence intervals associated with the ratios.[30] We resample with replacement from the time series of the vector $\mathbf{x}_t = (\boldsymbol{\beta}_{t-1}, \boldsymbol{\lambda}_t, \mathbf{Z}_{t-1})$ for a given asset. This preserves the relation between the component of the return $\boldsymbol{\beta}'_{t-1}\boldsymbol{\lambda}_t$ and the instruments $\mathbf{Z}_{t-1}$. We resample with replacement from

[29] The variance ratio VR1 is analogous to the coefficient of determination in a regression of the portfolio return on a set of proxy portfolios for the economic factors, where all the variables are projected onto the predetermined instruments. Previous studies examined regressions of ex post returns on such factor-mimicking portfolios. The covariance of returns can be decomposed into the covariance of the expected returns plus the covariance of the innovations. Because monthly stock returns are so noisy, the covariance of the innovations is by far the dominant component. Little can be inferred about the covariance of the expected returns on the basis of the ex post regressions because of the low "signal to noise ratio."

[30] The bootstrap experiments do not take account of potential spurious correlation between the estimation error in the risk premiums and the lagged instruments. Such correlation could arise from errors in the betas and could bias the variance ratios. Our appendix provides variance ratios that use alternative estimates for the betas. The main results are not sensitive.

the time series of the (mean-centered) residuals $u_t = r_t - \boldsymbol{\beta}'_{t-1}\boldsymbol{\lambda}_t$, and we form the pseudo return as the sum of the resampled $u_t + \boldsymbol{\beta}'_{t-1}\boldsymbol{\lambda}_t$.[31] The artificial data satisfy the hypothesis that the multibeta model captures the predictable variation of the returns using $\mathbf{Z}_{t-1}$.

For each sample of 272 observations, we regress the pseudo return, r_t, and the components of the return on $\mathbf{Z}_{t-1}$ and form the variance ratios:

$$\begin{aligned} \mathrm{VR1} &= \frac{\operatorname{var}[P(\boldsymbol{\beta}'_{t-1}\boldsymbol{\lambda}_t|\mathbf{Z}_{t-1})]}{\operatorname{var}[P(r_t|\mathbf{Z}_{t-1})]}, \\ \mathrm{VR2} &= \frac{\operatorname{var}[P(u_t|\mathbf{Z}_{t-1})]}{\operatorname{var}[P(r_t|\mathbf{Z}_{t-1})]}, \end{aligned} \tag{5}$$

where $P(\cdot|\mathbf{Z}_{t-1})$ stands for the sample values of a linear projection onto $\mathbf{Z}_{t-1}$ and var[·] is the sample variance. Repeating the experiment 1,000 times, we produce empirical distributions of the variance ratios. We use the empirical distributions to compute the one-tailed "p-values" in table 7. These are the fraction of the 1,000 values of the bootstrapped VR1 (VR2) below (above) the sample values recorded in the table.

The VR1 ratios produce only weak evidence against the hypothesis that the model captures all the predictable variation of the portfolio returns. Four of the 12 ratios for the industry portfolios imply p--values less than 10 percent, and none is less than 10 percent for the bonds. In the size portfolios, there is a concentration of low p-values for the smaller firms. The poor fit for the small firms is related to the January effect, as can be seen from the ratios in the third and fourth columns. There, the variance ratios are calculated without the January dummy variable in the set of instruments. The VR1's that result are closer to 1.0 (third column) and the VR2's are closer to 0.0 (fourth column) for the small firms.

Although 14 (six) of the 25 VR2 ratios imply p-values less than .10 (.05), the magnitudes of the ratios indicate that the proportion of the predictable variance not captured by the model is small. For the stocks, the VR2 is larger than 10 percent in only four of the 25 cases. It is clear that the VR1 ratios are much closer to 1.0 than to 0.0 and that the VR2 ratios are closer to 0.0 than to 1.0.[32]

Further experiments show that these results are robust to variations

[31] If the value for $\mathbf{x}_\tau$ is drawn, we remove u_τ and $u_{\tau-1}$ from the "urn" of the u's for time τ.

[32] The experiments show that the expected value of the variance ratio VR1 is less than 1.0 when the model captures 100 percent of the predictable variation of a return, and the expected value of VR2 is greater than zero. The empirical distributions of the ratios are leptokurtic, with more mass in the center than a normal distribution. Tables of summary statistics of the results of the bootstrap experiments are available by request.

on the methodology.[33] In one case, we constrained the betas to be nearly constant over time. In another experiment, we exclude the stock market index from the multiple-beta model. Even in these cases, the portion of the predictable variation that is not captured by the model is small. A large part of the predictable variation in the returns can be captured by the model. Thus the multiple-beta model provides a reasonable approximation of the predictable variation in the monthly rate of return data, even if it is not completely correctly specified.[34]

C. *Sources of Predictable Variation*

Given that the model captures most of the predictable variation of the returns, it is interesting to further decompose the predictable part. Two decompositions are presented: The first isolates the contributions of the individual economic variables; the second assesses the relative importance of changes in beta and changes in the price of beta. In the first case, the variance of the projection of $\Sigma_{j=1}^{K} \lambda_{jt}\beta_{ij,t-1}$ on the instruments is decomposed, for each asset i, into the sum of the variances attributable to each $\lambda_j\beta_{ij}$ term, $j = 1, \ldots, 6$, plus an interaction term due to covariance across the economic variables. The decompositions are estimated using the sample variances of the fitted values from linear regressions on $\mathbf{Z}_{t-1}$. The second decomposition can be expressed for asset i, using notation similar to equation (5), as follows:

$$\text{var}[P(\boldsymbol{\beta}_i'\boldsymbol{\lambda}|\mathbf{Z})] = \{E(\boldsymbol{\beta}_i)'\text{var}[P(\boldsymbol{\lambda}|\mathbf{Z})]E(\boldsymbol{\beta}_i)\} + \{E(\boldsymbol{\lambda})'\text{var}[P(\boldsymbol{\beta}_i|\mathbf{Z})]E(\boldsymbol{\lambda})\} + \text{interaction terms}, \tag{6}$$

where $E(\boldsymbol{\beta}_i)$ and $E(\boldsymbol{\lambda})$ are the unconditional means of the betas for asset i and the risk premiums, and the interaction terms arise because of covariance between the conditional expected risk premiums and the betas.

Table 8 presents the results of the variance decompositions. The first seven columns show the contributions of the individual economic variables. The variation associated with the expected stock market

[33] The details of these experiments are available in our appendix.

[34] In another experiment, we repeated the analysis using a bias-adjusted cross-sectional coefficient estimator and obtained results similar to those in table 7. We also examined the autocorrelations of the portfolio returns and of the two components provided by the model. This corresponds to using the lagged values as alternative information variables. We find that the autocorrelations of the components that are related to risk by the model are similar to those of the individual assets, while the autocorrelations of the components not related to risk are close to zero.

TABLE 8

DECOMPOSING THE PREDICTED VARIATION OF MONTHLY PORTFOLIO RETURNS, 1964:5–1986:12 (272 Observations)

	Decomposition by Economic Risk Variables							Decomposition by Betas vs. Price of Beta		
Portfolio	XVW	PREM	ΔSLOPE	UI	CGNON	REALTB	Interaction Effects	Changing Beta	Changing Price of Beta	Interaction Effects
Decile:										
1	45.19	6.09	4.74	9.16	.31	23.22	11.29	1.41	67.80	30.79
2	51.42	3.90	3.00	5.59	.25	17.50	18.34	1.20	68.58	30.22
3	58.59	3.13	2.53	3.39	.15	14.38	17.83	1.31	75.32	23.37
4	64.45	1.45	2.01	2.57	.36	12.06	17.10	.85	78.71	20.44
5	69.68	1.81	1.43	1.99	.16	8.47	16.46	.46	80.03	19.51
6	80.05	.87	1.28	2.00	.19	8.36	7.25	.25	85.66	14.09
7	89.44	.38	.61	1.34	.12	3.62	4.49	.16	91.62	8.22
8	85.98	.38	.67	1.50	.14	5.32	6.01	.25	89.58	10.17
9	97.13	.20	.39	2.65	.14	1.78	−2.29	.04	90.87	9.09
10	105.45	.10	.26	.47	.06	1.36	−7.70	.04	111.44	−11.48
Industry:										
Petroleum	150.64	1.91	1.80	67.18	6.80	149.50	−277.83	.83	146.67	−47.49
Finance/real estate	112.22	1.32	.20	7.18	1.80	6.36	−29.08	.42	101.46	−1.88
Consumer durables	87.95	.89	.87	4.12	.73	15.90	−10.42	.04	93.87	6.09
Basic industries	89.07	.10	.22	2.01	1.91	4.09	2.60	.05	95.80	4.15
Food/tobacco	82.11	.96	.52	5.81	1.50	15.90	−6.80	.37	89.24	10.39
Construction	90.03	1.43	.66	4.80	.52	8.44	−5.88	.33	83.40	16.27
Capital goods	75.32	.61	1.11	15.26	3.20	13.07	−8.57	3.14	97.24	−.38
Transportation	75.47	.67	4.28	6.49	1.56	6.25	5.28	.66	84.03	15.31
Utilities	87.61	5.56	4.28	9.41	13.60	8.27	−28.73	1.73	87.66	10.61
Textiles/trade	65.80	.27	.37	7.73	6.37	35.00	−15.54	.15	80.40	19.45
Services	74.88	.44	.37	7.19	.32	20.71	−3.91	.75	68.66	30.59
Leisure	73.12	.10	1.31	17.07	1.13	43.64	−36.37	.80	84.01	15.19
Government bonds	7.23	132.27	3.24	1.96	6.56	9.23	−60.47	1.68	91.93	6.39
Corporate bonds	18.34	92.70	6.73	13.21	21.77	20.07	−72.82	3.92	59.83	36.25
6-month Treasury bill	.53	39.74	60.74	12.04	5.40	18.76	−37.21	1.19	46.16	52.65

NOTE.—All rates of return are in excess of the 1-month Treasury bill rate. Decile 1 represents the excess returns on the decile of the smallest-valued firms on the NYSE. Decile 10 represents the excess returns on the largest decile of NYSE stocks. The figures are the percentages of the sample variances of predicted excess returns, using a multibeta asset pricing model, which are allocated to different sources of predictable variation.

premium is the most important for the predictability of the equity returns. It captures a smaller portion of the movements in the expected returns of the smaller firms. For the bond returns, the contribution of the market factor is small.

The influence of the real interest rate premium is the largest in the petroleum industry, where it is almost as important as the stock market. It contributes more than 20 percent for three other industries and for the small-firm stock portfolio. The interest rate–related variables and inflation risk tend to explain larger portions for the smaller firms. A large part of the predictability of long-term bonds is attributed to the PREM variable, while the premium for the term structure variable ΔSLOPE is the most important for the 6-month Treasury bill.

The last three columns of table 8 show that most of the predicted variation of the expected returns is associated with variation in the price of beta risk. Very little of the variance is attributed to independent movements in the betas.[35] The interaction effect, which reflects predictable covariation between betas and risk premiums, accounts for some of the variance of the smaller firms, a few of the industries, and the 6-month Treasury bill.

D. *Interpreting the Evidence*

The finding that most of the predictable variation in the portfolio returns may be attributed to changes in the market price of beta risk has implications for the formulation of time-varying asset pricing models. The evidence suggests that the constant beta assumption made in "latent variables" models (see Hansen and Hodrick 1983; Gibbons and Ferson 1985; Ferson 1990) may be a reasonable approximation to the data. However, this does not imply that the predictable variation is unrelated to changes in risk. Consider the intertemporal asset pricing model of Merton (1973, eq. 32), which can be written (without time subscripts) as

$$E(r_i) = \beta_{im}\left(\frac{-WJ_{ww}}{J_w}\right)\operatorname{var}\left(\frac{dW}{W}\right) + \sum_{s=1}^{K}\beta_{is}\left(\frac{-J_{ws}}{J_w}\right)\operatorname{var}(ds). \quad (7)$$

The risk premium for the market beta is $(-WJ_{ww}/J_w)\operatorname{var}(dW/W)$, and the price of beta for state variable s is $(-J_{ws}/J_w)\operatorname{var}(ds)$, where $J(\cdot)$ is the indirect marginal utility of wealth, W is wealth, and the subscripts on $J(\cdot)$ denote its partial derivatives. The price of beta depends both on risk aversion for the state variable and on the conditional variance

[35] Our appendix shows that this result is robust to alternative beta estimators.

of the state variable. Changes in the price of beta are driven by both of these factors.

Previous studies document time variation in beta coefficients for individual stocks and suggest that changes in the betas can be important at the firm level.[36] Portfolios of common stocks are more stable, in terms of relative risk, than individual stocks.[37] But estimates of the portfolio betas still fluctuate over time. For example, time-series regressions of the 5-year rolling betas on our lagged instruments typically produce adjusted R^2's near 20 percent. Most of the R^2's exceed 10 percent, and numbers as high as 50–60 percent are observed. Both the cross-sectional structure and the level of the betas vary over the sample.

The interaction effect between changes in the betas and changes in the price of beta in table 8 is the largest for the smallest firms, declines nearly monotonically as the size of the firms increases, and is negative for the largest firms. This suggests that smaller firms' betas are more positively related to expected risk premiums and thus tend to be relatively high in recessions when expected premiums are high, while the largest firms' betas tend to be relatively low at such times.[38]

Given that the portfolio betas exhibit significant time variation, it may seem puzzling that the decompositions attribute so little to variation in the betas. In a decomposition, the variance of the beta is multiplied by the square of an average risk premium. The largest average risk premium in table 5 is less than 0.007. The square of this number scales down the variance of the betas. In contrast, the component attributed to a time-varying expected risk premium depends on the variance of the conditional expected premium multiplied by the square of an average beta. The variance of an expected risk premium is on the order of the variance of a portfolio expected return, and the betas are on the order of 1.0. Thus it is not surprising that most of the predictable variation is attributed to time-varying risk premiums as opposed to time-varying betas. When one thinks of the sources of predictable variation in this way, what is

36 Chan (1988) and Ball and Kothari (1989) show that changes in market beta coefficients can explain much of the mean reversion phenomenon for individual common stocks that are recent "winners" or "losers." Ball and Kothari find that individual firms' market betas commonly halve or double after a period of unusually large price rises or declines.

37 For evidence on size portfolios, see Huberman and Kandel (1987) and Chan and Chen (1988). Much of the variation of individual firms' betas is probably diversified out at the level of industry portfolios as well.

38 Chan and Chen (1988) use a model that assumes such a cross-sectional pattern of the movements in betas over time to explain the observation that the average returns of small firms are too high, and the returns of large firms are too low, relative to unconditional versions of the CAPM.

surprising is that so much research effort has gone into modeling the time series of betas and so little attention has been directed toward modeling the time-series behavior of the price of beta.

V. Concluding Remarks

Measures of economic risk that have been identified with average risk premiums can also capture predictable variation in asset returns. Much of the predicted variation of monthly excess returns of size- and industry-grouped common stock portfolios is associated with their sensitivity to these economic variables. Time variation in the expected compensation for beta, as opposed to movements in the betas, captures most of the predicted variation at the portfolio level. Among a group of six economic variables, the risk premium associated with a stock market index captures the largest component of the predictable variation in the stock returns. The premiums associated with term structure shifts and default spreads are the most important for the fixed-income securities. Our findings strengthen the evidence that the predictability of returns is attributable to time-varying, rationally expected returns.

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