EXPLAINING THE PREDICTABILITY OF ASSET RETURNS[1]

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ABSTRACT

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

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others maintain that predictability is the result of changes in the required return. In this 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 which 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 market-wide 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 which 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 which 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 the fourth section. Section V summarizes our conclusions. An appendix examines the robustness of the results to variations in the methodology.

II. METHODOLOGY

We study models which 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 Constantinides, 1980; Merton, 1973; and Sharpe, 1964]:

$$E(R_{it} \mid Z_{t-1}) = \gamma_0(Z_{t-1}) + b_{im,t-1}\, \gamma_m(Z_{t-1}), \tag{1}$$

where R_{it} is the rate of return of asset i between times $t-1$ and t, and $b_{im,t-1}$ 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. Z_{t-1} is the conditioning information, assumed to be publically available at time $t-1$. $\gamma_m(Z_{t-1})$ is the price of market beta, and $\gamma_0(Z_{t-1})$ is the expected return of all portfolios with market beta equal to zero. If there is a risk-free asset available at time $t-1$, its rate of return equals $\gamma_0(Z_{t-1})$.

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 Z_{t-1}, the model implies that either the betas or the premiums, $\gamma_m(Z_{t-1})$ and $\gamma_0(Z_{t-1})$, are changing as functions of Z_{t-1}.

A. The Cross-Sectional Regression Approach

Cross-sectional regression methods similar to 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 actual asset returns on the betas. We conduct our analysis using *excess returns* $r_{it} = R_{it} - R_{ft}$, where R_{ft} is the return of a one-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.[2]

The cross-sectional regression equation for month t is

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

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 due to the component that is related to risk. The part of the return that is unrelated to risk should be unpredictable.[3]

B. Generalizing to Multiple Betas

The 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.[4] A multiple-beta model asserts the existence of expected premiums $\gamma_j(Z_{t-1})$, $j = 0, \ldots, K$, such that expected returns, conditional on the information Z_{t-1}, can be written as

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

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 will specify proxies for the state variables.[5]

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

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

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, λ_{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, $\gamma_j(Z_{t-1})$, 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.

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, predictable variation in the misspecification can contaminate the $\lambda_{0t} + e_{it}$ component.[6] It is conceivable that inefficiencies are systematically related across assets to differences in the betas and are predictable using 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 $\lambda_{0t} + e_{it}$.[7] 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 the appendix we examine the sensitivity of our results to the way in which the betas are estimated.

Even if the "true" betas were known, the second-step, cross-sectional regressions are complicated because the returns are correlated and heteroscedastic. 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 WLS regressions, where 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 (1992).[10]

Errors in the variables could affect our inferences from using the fitted premiums as dependent variables in time-series regressions to assess predictability. Even if the premium estimates were unbiased, estimation error in the premiums would distort the standard errors.[11] 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.

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, which are described in the Appendix, 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 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, a long-term corporate bond, and the Treasury bill that is the closest to six months to maturity. The data are provided by the Center for Research in Security Prices at the University of Chicago (CRSP). Ten common stock portfolios are formed according to size deciles, based on the market value of equity outstanding at the beginning of each year. The ten "size" portfolios are value-weighted averages of the firms. (Value weighing approximates a "buy-and-hold" investment strategy.) We also include 12 portfolios of NYSE firms grouped by 2-digit SIC industry code. Unlike 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 is recorded by CRSP. The portfolios are value weighted each month. Table 1 presents the SIC codes of the industry groups.

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 which found that the average price of beta for such variables was nonzero.[13] 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 which determine security returns. But the specific variables are of some economic interest.

Table 1. Industry Portfolio Groups

Portfolio Number	*2-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

Table 2. The Economic Variables

Symbol	Definition	Source
XVW	Value-weighted NYSE index return less one-month Treasury bill return	CRSP
CGNON	Monthly real, per capita growth of personal nondurables consumption expenditures, 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 ten-year Treasury bond and a three-month Treasury bill	Federal Reserve Bulletin
UI	Unexpected inflation rate is the difference between the actual and the forecasted inflation rate, formed from a time-series model for percentage changes in the consumer price index for all urban consumers, not seasonally adjusted	CRSP
REALTB	One-month Treasury bill return less the monthly rate of inflation, as measured by the CPI	CRSP

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. XVW is the return of the CRSP value-weighted stock market index in excess of a one-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. REALTB is the real, one-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) and Lucas (1978) and Breeden (1979) imply that "priced" state variables must covary with aggregate marginal utility. Marginal utility should vary directly with changes in aggregate consumption when markets are complete and perfect and utility is time separable. Breeden et al. (1989) found that consumption betas are useful in describing a cross section of average returns. 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. UI is the unexpected inflation rate measured as the residual from a time-series model for the percentage changes in the consumer price index.[14]

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.[15] Chen et al. (1986), and Chan et al. (1985) propose such a state variable as a measure of changes in the risk of corporate default.[16]

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

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.

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

HB3(-1) is the one-month return of a three-month Treasury bill less the one-month return of a one-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.

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. Fama and French (1988b, 1989), Campbell and Shiller (1988), and others examine similar variables. DIV(-1) 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

Table 3. The Instruments

Symbol	*Definition*	*Source*
XEW(-1)	Equal-weighted NYSE index return less one-month Treasury bill return	CRSP
HB3(-1)	One-month return of a three-month Treasury bill less the one-month return of a one-month bill	CRSP Fama (1984)
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, one-month Treasury bill rate	CRSP

stock market. Mean reversion suggests that if stock returns are below average (so that prices are relatively low and yields are high), expected returns may be higher than average.

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.

TB1 is the nominal, one-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.[17]

The predetermined variables follow empirical work using 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,[18] 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

Summary statistics for the size portfolios and the bonds are familiar from previous studies and are not reported here. 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 to 0.2). But the autocorrelations of some of the instruments are significantly higher.[19]

We estimate the predictable part of the returns by regressing them on the predetermined variables. These regressions are reported in Table 4. The signs and magnitudes of the regression coefficients are not surprising, given earlier studies. 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 smaller for the bond returns. JUNK(-1) has a strong positive relation with most of the returns. TB1 enters with negative coefficients. The adjusted R-squares exceed 4% for each of the 25 portfolio returns and 16 of the 25 exceed 10%. These figures refer to regressions which include a dummy variable for the month of January. When we do not include a January dummy, the adjusted R-squares range from 3.8 to 13.2%, and 15 of the 25 are larger than 10%. Thus, the predetermined variables uncover

Table 4. Regressions of the Asset Returns on the Instrumental Variables: 1964:5–1986:12 (272 Observations)

Portfolio	δ_0	δ_1 *XEW*	δ_2 *JAN*	δ_3 *HB3*	δ_4 *JUNK*	δ_5 *DIV*	δ_6 *TB1*	$\bar{R}^2$
Deciles: 1	–0.0434	0.0748	0.0972	3.1666	13.8445	27.2966	–11.0800	0.196
(smallest)	(0.0181)	(0.1213)	(0.0290)	(2.7485)	(12.1305)	(7.0324)	(3.2647)	
2	–0.0451	0.0322	0.0715	3.0991	16.3240	27.2154	–10.9140	0.185
	(0.0153)	(0.0725)	(0.0231)	(2.4609)	(10.4568)	(5.9675)	(2.6249)	
3	–0.0426	0.0342	0.0573	2.9532	19.4687	25.6357	–10.9450	0.170
	(0.0140)	(0.0650)	(0.0204)	(2.4623)	(9.6335)	(5.6678)	(2.4203)	
4	–0.0373	0.0303	0.0424	3.7898	16.4669	24.0872	–10.3010	0.152
	(0.0135)	(0.0580)	(0.0185)	(2.2883)	(9.2004)	(5.5247)	(2.0786)	
5	–0.0337	0.0154	0.0375	4.7426	18.0039	21.5385	–9.8739	0.153
	(0.0127)	(0.0534)	(0.0166)	(2.1357)	(8.6930)	(5.0690)	(2.0122)	
6	–0.0330	0.0019	0.0304	4.1425	17.9104	20.4186	–9.2203	0.133
	(0.0123)	(0.0495)	(0.0159)	(2.2736)	(8.0990)	(5.0940)	(2.0108)	
7	–0.0306	–0.0094	0.0168	4.0797	19.8036	20.3725	–9.8471	0.126
	(0.0125)	(0.0433)	(0.0145)	(2.5981)	(8.2731)	(5.3368)	(1.9781)	
8	–0.0283	–0.0532	0.0163	4.9070	16.4701	18.4448	–8.6660	0.112
	(0.0119)	(0.0424)	(0.0142)	(2.4234)	(7.9595)	(5.2495)	(1.9099)	
9	–0.0260	0.0485	0.0094	5.0599	16.2634	16.6767	–8.1060	0.108
	(0.0118)	(0.0364)	(0.0123)	(2.8518)	(7.7316)	(5.1665)	(1.7772)	
10	–0.0156	–0.0643	–0.0006	4.7572	17.8358	11.3832	–7.2093	0.105
(Largest)	(0.0094)	(0.0291)	(0.0104)	(3.2146)	(6.7875)	(4.1301)	(1.2134)	
Petroleum	–0.0122	–0.0867	–0.0107	6.5741	5.4297	14.5125	–7.1505	0.058
	(0.0189)	(0.0424)	(0.0130)	(4.1242)	(11.0616)	(7.8970)	(1.8498)	
Finance/real estate	–0.0244	–0.0980	0.0029	5.4528	13.3902	16.5077	–7.6807	0.086
	(0.0119)	(0.0420)	(0.0121)	(2.8933)	(8.2479)	(4.9194)	(1.7635)	
Consumer durables	–0.0324	–0.0079	0.0132	1.5609	31.6637	18.8074	–10.796	0.130
	(0.0111)	(0.0381)	(0.0161)	(2.6088)	(8.0526)	(5.1374)	(1.8581)	
Basic industries	–0.0106	–0.0417	0.0080	7.1504	14.0048	9.5120	–6.5697	0.093
	(0.0101)	(0.0365)	(0.0113)	(3.3525)	(7.4362)	(4.9464)	(1.6422)	
Food/tobacco	–0.0199	–0.0833	0.0066	5.0979	19.6268	10.6504	–5.7929	0.091
	(0.0077)	(0.0399)	(0.0101)	(2.7649)	(6.6554)	(3.6211)	(1.6148)	

(continued)

Table 4. (continued)

Portfolio	δ_0	δ_1 *XEW*	δ_2 *JAN*	δ_3 *HB3*	δ_4 *JUNK*	δ_5 *DIV*	δ_6 *TB1*	$\bar{R}^2$
Construction	−0.0298	0.0470	0.0193	5.5829	25.7487	17.3985	−10.018	0.137
	(0.0152)	(0.0563)	(0.0167)	(2.8565)	(9.4193)	(5.9767)	(1.6542)	
Capital goods	(−0.0140)	(0.0131)	(0.0093)	(4.2106)	(18.5180)	14.7512	−9.6302	0.113
	(0.0107)	(0.0528)	(0.0142)	(3.7945)	(8.8326)	(5.0260)	(1.7140)	
Transportation	−0.0304	−0.0068	0.0254	7.3807	19.6246	17.6855	−9.2070	0.104
	(0.0164)	(0.0525)	(0.0147)	(3.4166)	(10.9775)	(5.9228)	(1.9963)	
Utilities	−0.0207	−0.1340	0.0135	3.0503	18.2581	9.1749	−4.8790	0.098
	(0.0088)	(0.0373)	(0.0085)	(1.9656)	(5.7301)	(3.3020)	(1.2421)	
Textiles/trade	−0.0272	−0.0569	0.0130	3.4173	35.2866	12.4026	−8.3846	0.095
	(0.0123)	(0.0521)	(0.0163)	(2.2872)	(9.5263)	(5.4286)	(2.1938)	
Services	−0.0543	−0.0079	0.0191	2.5793	19.5778	31.1010	−11.973	0.110
	(0.0170)	(0.0639)	(0.0179)	(3.9872)	(11.0971)	(6.1997)	(2.5702)	
Leisure	−0.0381	0.0577	0.0099	3.5349	20.2785	24.6565	−10.937	0.102
	(0.0139)	(0.0591)	(0.0185)	(2.7564)	(11.4275)	(6.1495)	(2.9930)	
Government bonds	−0.0116	−0.1095	−0.0084	1.8760	10.0908	4.9457	−2.5690	0.040
	(0.0063)	(0.0405)	(0.0060)	(1.4766)	(5.9682)	(3.5315)	(1.1874)	
Corporate bonds	−0.0125	−0.1057	0.0008	2.1640	11.9924	5.4036	−3.1196	0.055
	(0.0067)	(0.0415)	(0.0064)	(1.4796)	(5.9430)	(3.6457)	(1.2341)	
Six-month Treasury bill	−0.0011	−0.0134	0.0004	0.4183	0.6773	0.4339	−0.0580	0.092
	(0.0007)	(0.0052)	(0.0004)	(0.1842)	(0.5812)	(0.3456)	(0.1195)	

Notes: The model estimated is

$$r_{it} = \delta_0 + \delta_1 XEW_{t-1} + \delta_2 JAN_t + \delta_3 HB3_{t-1} + \delta_4 JUNK_{t-1} + \delta_5 DIV_{t-1} + \delta_6 TB1_t + \varepsilon_{it},$$

where r_{it} represents the return on asset i. Standard errors in parentheses are corrected for a moving average process of order MA(11) and conditional heteroscedasticity. $\bar{R}^2$ is the (adjusted) coefficient of determination for the regression of the fitted risk premiums on the predetermined instrument. The instruments are a constant, the lagged excess return on the equally weighted NYSE index (XEW), a dummy variable for the month of January (JAN), the lagged return for holding a 90-day bill for one month less the return on a 30 day bill (HB3), the lagged yield on Moody's Baa rated bonds less the yield on Moody's Aaa rated bonds (JUNK), the lagged dividend yield on the Standard and Poor's 500 stock index (DIV) and the return on a one month Treasury bill (TB1).

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 persistent 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 are between REALTB and UI (–0.698) and between UI and XVW (–0.218). Only three of the contemporaneous correlations among the instruments exceed 0.5, and the largest is 0.74.

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 are for the "non-market" risk associated with the economic variables. Using only the bond returns and the ten size-ranked stock portfolios, 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 previous studies. But the premium for the PREM variable is smaller than reported by Chan et al. (1985) and Chen et al. (1986).[20] *T*-statistics greater than 2.0 are recorded for XVW and REALTB in the bivariate models. The *t*-ratios for PREM (1.80) and ΔSLOPE (1.92) are close to 2.

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 6 economic variables. *T*-statistics near 2.0 are recorded for PREM, ΔSLOPE, and CGNON, and all the signs of the mean premium estimates are unchanged.[21] 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 small average premium, Chen et al. argue that other economic variables largely subsume the market premium.

Table 5. Average Risk Premiums Associated with Economic Variables (in Percent per Month) For 1964:5–1986:12 (172 Observations)

Variable[a]	XVW	PREM	ΔSLOPE	UI	CGNON	REALTB
Bivariate models						
Size and bond portfolios	0.693[b]	0.422	0.026	–0.130	0.135	0.175
	(2.23)[b]	(1.80)	(1.92)	(–1.71)	(0.53)	(2.42)
Industry, size and bond portfolios	0.471†	0.447	0.018	–0.089	0.319	0.103
	(1.61)†	(2.01)	(2.57)	(–1.81)	(2.11)	(2.16)
Multivariate model						
Industry, size and bond portfolios	0.272	0.378	0.020	–0.043	0.328	0.040
	(1.07)	(1.94)	(2.47)	(–0.93)	(2.14)	(0.84)

Notes: The model is

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

where β_{ij} is the ith asset's sensitivity to the jth macroeconomic 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}. T-statistics for the average of the risk premiums over time are in parentheses. These are calculated from the time series of the estimates of λ_{jt}.

[a]XVW is the excess return on the value-weighted NYSE index. PREM is the difference of the returns on Baa corporate bonds and government bonds. ΔSLOPE is the first difference of the yield spread between a 10-year Treasury and a 3-month Treasury—both average yields over the month, UI is the unexpected rate of change in the not seasonally adjusted consumer price index (based on a time-series model of inflation). CGNON is the growth in per capita personal consumption of nondurables (seasonally adjusted), REALTB is the real return on a one-month Treasury bill.

[b]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 are from a cross-sectional model estimated with only one risk measure.

A. Predictable Variation in Risk Premiums

Table 6 summarizes time-series regressions of the fitted premiums on the predetermined information variables.[22] 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%. 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 univariate 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.[23] 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

Table 6. Regressions of the Risk Premiums on the Instrumental Variables: 1964:5–1986:12 (272 Observations)

Premium	δ_0	δ_1 XEW	δ_2 JAN	δ_3 HB3	δ_4 JUNK	δ_5 DIV	δ_6 TB1	$\bar{R}^2$ (%)
Bivariate models								
XVW[a]	–0.03	0.09	0.03	1.81	10.39	17.62	–7.93	14.0
	(0.01)	(0.05)	(0.01)	(2.03)	(8.03)	(5.31)	(2.02)	
PREM	0.01	0.04	0.05	–0.90	–6.62	2.56	–2.05	12.4
	(0.01)	(0.06)	(0.01)	(1.61)	(6.83)	(4.01)	(1.71)	
ΔSLOPE	–0.00	–0.00	0.00	0.01	0.23	–0.06	0.03	2.0
	(0.00)	(0.00)	(0.00)	(0.05)	(0.15)	(0.15)	(0.05)	
UI	0.00	0.01	–0.01	0.66	–1.06	–1.62	0.38	6.9
	(0.00)	(0.02)	(0.00)	(0.47)	(1.54)	(1.01)	(0.37)	
CGNON	–0.01	0.02	0.03	–1.41	–5.08	5.72	–0.56	8.9
	(0.01)	(0.03)	(0.01)	(1.05)	(5.88)	(2.22)	(1.12)	
REALTB	–0.01	–0.01	0.01	–0.55	1.23	2.12	–0.45	9.5
	(0.00)	(0.01)	(0.00)	(0.38)	(1.52)	(1.10)	(0.42)	
Multivariate model								
XVW	–0.03	0.01	0.00	3.63	14.38	14.57	–6.73	9.9
	(0.01)	(0.04)	(0.01)	(2.42)	(8.03)	(5.07)	(1.51)	
PREM	0.00	0.05	0.04	–1.90	0.90	–0.42	–0.44	10.5
	(0.01)	(0.04)	(0.01)	(1.82)	(5.97)	(4.25)	(1.62)	
ΔSLOPE	0.00	–0.00	0.00	0.07	0.14	–0.05	–0.02	0.0
	(0.00)	(0.00)	(0.00)	(0.07)	(0.17)	(0.13)	(0.04)	
UI	0.00	0.01	–0.00	0.78	–1.51	–0.92	–0.03	3.6
	(0.00)	(0.01)	(0.00)	(0.43)	(1.46)	(0.81)	(0.33)	
CGNON	–0.00	0.02	0.02	–2.27	–0.14	0.09	0.75	2.2
	(0.01)	(0.03)	(0.01)	(1.26)	(5.01)	(2.64)	(1.08)	
REALTB	–0.01	–0.01	0.01	–0.93	2.63	1.08	–0.01	7.4
	(0.00)	(0.01)	(0.00)	(0.41)	(1.86)	(0.94)	(0.34)	
Sum of premiums	–0.02	0.08	0.06	–0.61	16.40	14.35	–6.48	10.4
	(0.01)	(0.06)	(0.02)	(3.93)	(11.24)	(7.08)	(2.84)	
Value-weighted market return	–0.02	–0.05	0.01	4.88	17.21	14.35	–7.81	11.6
	(0.01)	(0.03)	(0.01)	(2.98)	(7.06)	(4.32)	(1.37)	

Notes: The model estimated is

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

where λ_{jt} represents the risk premium associated with the economic variable in the first column.

Standard errors in parentheses are corrected for a moving average process of order MA(11) and conditional heteroscedasticity. $\bar{R}^2$ is the (adjusted) coefficient of determination for the regression of the fitted risk premiums on the predetermined instruments. The instruments are a constant, the lagged excess return on the equally weighted NYSE index (XEW), a dummy variable for the month of January (JAN), the lagged return for holding a 90-day bill for one month less the return on a 30-day bill (HB3), the lagged yield on Moody's Baa rated bonds less the yield on Moody's Aaa rated bonds (JUNK), the lagged dividend yield on the Standard and Poor's 500 stock index (DIV), and the return on a one-month Treasury bill (TB1).

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-squares indicate predictable time variation, so the expected premiums could be important at some times.[24] The expected premium 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 the regressions significantly.

Figures 1–5 plot the time series of the fitted expected risk premium associated with the stock market index and four other risk factors.[25] The dashed line represents the values in January and the solid line plots the other eleven months. The vertical lines denote reference business cycles determined by the National Bureau of

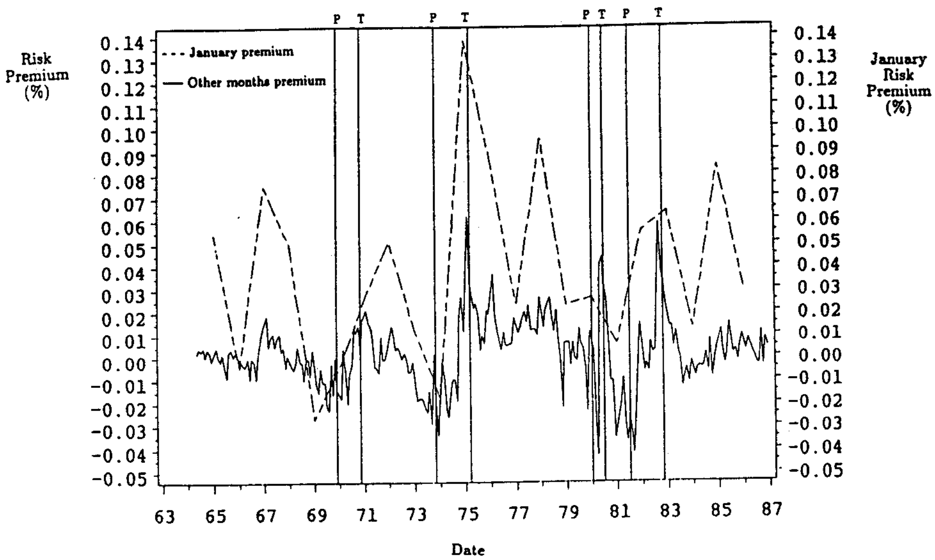

Figure 1. Fitted values from a regression of the price of market beta on the instrumental variables. The values for the price of market beta are the estimated coefficients from a cross-sectional regression each month of 25 portfolio returns on estimates of the beta coefficients for economic variable *XVW*. 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 which 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 is the January observations; the solid line is the other eleven months. The vertical lines denote NBER reference business cycle peaks (P) and troughs (T).

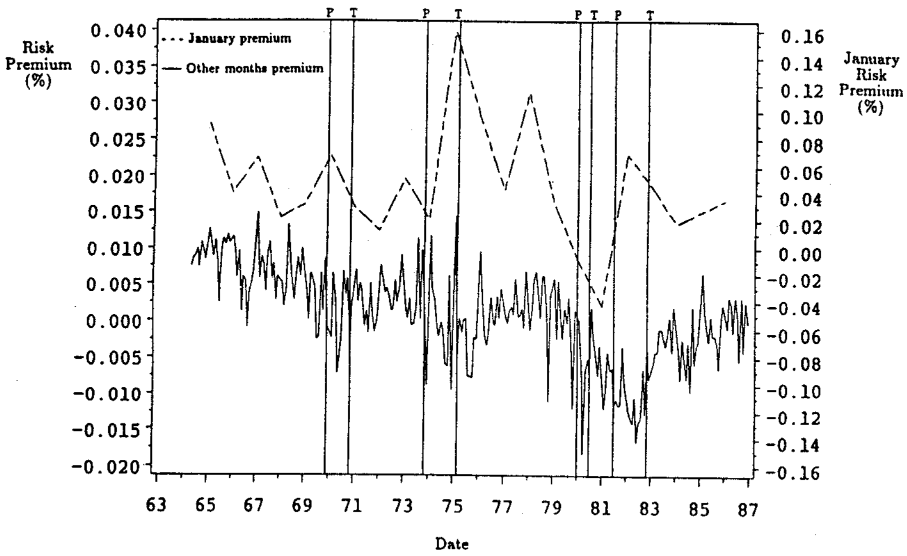

Figure 2. Fitted values from a regression of the price of default risk beta on the instrumental variables. The values for the price of market beta are the estimated coefficients from a cross-sectional regression each month of 25 portfolio returns on estimates of the beta coefficients for economic variable *PREM*. 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 which 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 is the January observations; the solid line is the other eleven months. The vertical lines denote NBER reference business cycle peaks (P) and troughs (T).

Economic Research (NBER). Of course, market expectations of economic conditions could differ from the ex post determination of business cycles by the NBER. Figure 1 suggests that the expected market 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.

When we use the predetermined variables to predict the "non-market" premiums from the bivariate models, most of the fitted values appear to have countercyclical patterns, as can be seen in Figures 2–5. 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

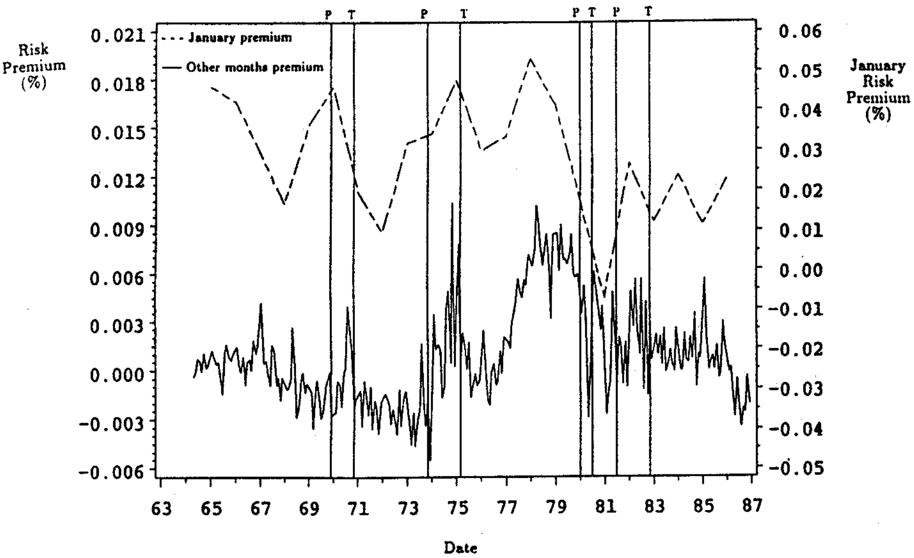

Figure 3. Fitted values from a regression of the price consumption beta on the instrumental variables. The values for the price of market beta are the estimated coefficients from a cross-sectional regression each month of 25 portfolio returns on estimates of the beta coefficients for economic variable *CGNON*. 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 which 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 is the January observations; the solid line is the other eleven months. The vertical lines denote NBER reference business cycle peaks (P) and troughs (T).

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, 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 0 and 1 would average the seasonal and cyclical patterns.

Figure 1 shows that the behavior of the fitted stock market risk premium in January roughly mirrors the behavior in the other eleven months, but at a higher level. We observe a similar pattern in most of the other premiums.[27] 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 which may produce cyclical variation in the other months are also at work in the January premium.

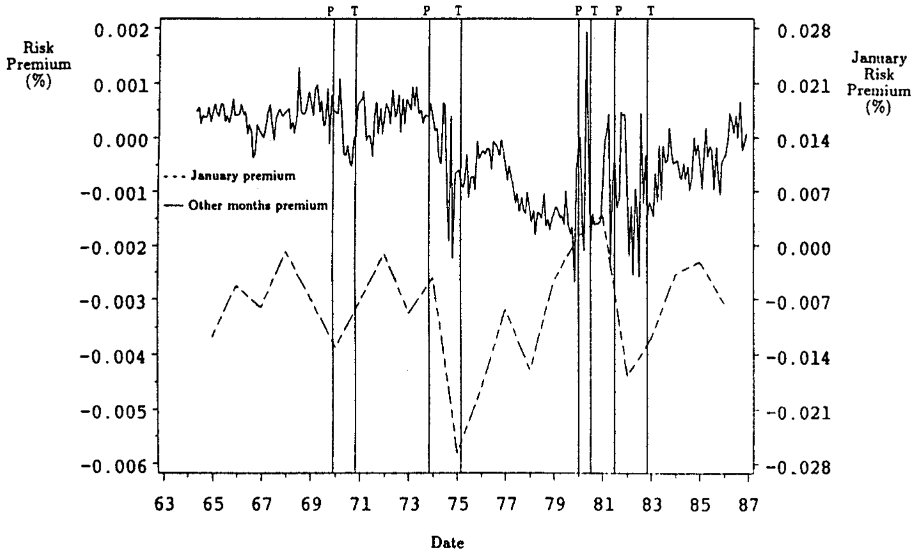

Figure 4. Fitted values from a regression of the price of unexpected inflation beta on the instrumental variables. The values for the price of market beta are the estimated coefficients from a cross-sectional regression each month of 25 portfolio returns on estimates of the beta coefficients for economic variable *UI*. 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 which 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 is the January observations; the solid line is the other eleven months. The vertical lines denote NBER reference business cycle peaks (P) and troughs (T).

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 instruments, 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 Z_{t-1}. This variance is also expressed as a ratio, VR2, relative to the total variance of the fitted expected return.[28]

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

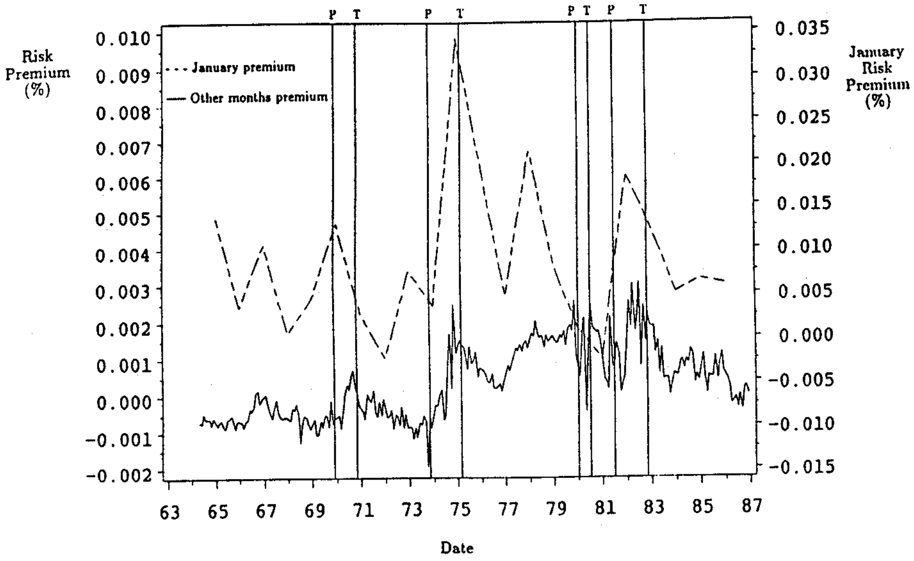

Figure 5. Fitted values from a regression of the price of real interest rate beta on the instrumental variables. The values for the price of market beta are the estimated coefficients from a cross-sectional regression each month of 25 portfolio returns on estimates of the beta coefficients for economic variable *REALTB*. 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 which 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 is the January observations; the solid line is the other eleven months. The vertical lines denote NBER reference business cycle peaks (P) and troughs (T).

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% 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.[29] We resample with replacement from the time series of the vector $x_t = (\beta_{t-1}, \lambda_t, Z_{t-1})$ for a given asset. This preserves the relation between the component of the return $\beta_{t-1}'\lambda_t$, and the instruments Z_{t-1}. We resample with replacement from the time series of the (mean centered) residuals

$u_t = r_t - \beta_{t-1}'\lambda_t$, and we form the pseudo-return as the sum of the resampled $u_t + \beta_{t-1}'\lambda_t$.[30] The artificial data satisfy the hypothesis that the multibeta model captures the predictable variation of the returns using Z_{t-1}.

For each sample of 272 observations we regress the pseudo return r_t and the components of the return on Z_{t-1} and form the variance ratios:

$$\mathrm{VR1} = \mathrm{var}\{P(\beta_{t-1}'\lambda_t \mid Z_{t-1})\}/\mathrm{var}\{P(r_t \mid Z_{t-1})\}, \text{ and} \tag{5}$$

$$\mathrm{VR2} = \mathrm{var}\{P(u_t \mid Z_{t-1})\}/\mathrm{var}\{P(r_t \mid Z_{t-1})\},$$

where $P(. \mid Z_{t-1})$ stands for the sample values of a linear projection onto Z_{t-1} and var{.} is the sample variance. Repeating the experiment 1000 times, we produce empirical distributions of the variance ratios.[31] We use the empirical distributions to compute the one-tailed p values in Table 7. These are the fraction of the 1000 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%, and none is less than 10% 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 which 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 (6) of the 25 VR2 ratios imply p values less than 0.10 (0.05), 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% in only 4 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.

Further experiments show that these results are robust to variations on the methodology. 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.[32]

C. Sources of Predictable Variation

Given that the model captures much of the predictable variation of the returns, it is interesting to further decompose the predictable part. Two decompositions are

Table 7. Decomposition of the Predictable Variation of Monthly Portfolio Returns: 1964:5–1986:12 (272 Observations)

Portfolio	*Including January Dummy Indicator* $\frac{var[P(\hat{\lambda}\hat{\beta} \mid Z)]}{var[P(r \mid Z)]}$ *(VR1)*	$\frac{var[P(r-\hat{\lambda}\hat{\beta} \mid Z)]}{var[P(r \mid Z)]}$ *(VR2)*	*Excluding January Dummy Indicator* $\frac{var[P(\hat{\lambda}\hat{\beta} \mid Z^0)]}{var[P(r \mid Z^0)]}$ *(VR1)*	$\frac{var[P(r-\hat{\lambda}\hat{\beta} \mid Z^0)]}{var[P(r \mid Z^0)]}$ *(VR2)*
Decile 1	0.644[.000][a]	0.071[.009][b]	0.901	0.016
Decile 2	0.744[.000]	0.045[.005]	0.922	0.014
Decile 3	0.751[.002]	0.028[.055]	0.810	0.021
Decile 4	0.822[.048]	0.019[.339]	0.846	0.019
Decile 5	0.796[.016]	0.029[.090]	0.820	0.029
Decile 6	0.822[.039]	0.025[.222]	0.855	0.022
Decile 7	0.792[.025]	0.035[.119]	0.783	0.037
Decile 8	0.884[.137]	0.050[.037]	0.894	0.051
Decile 9	0.842[.092]	0.048[.105]	0.852	0.046
Decile 10	0.806[.112]	0.082[.074]	0.801	0.078
Industry 1	0.639[.040]	0.059[.491]	0.631	0.061
Industry 2	0.798[.156]	0.101[.078]	0.797	0.091
Industry 3	0.738[.015]	0.069[.067]	0.735	0.071
Industry 4	0.960[.527]	0.137[.029]	0.974	0.134
Industry 5	0.810[.182]	0.121[.081]	0.819	0.119
Industry 6	0.667[.005]	0.050[.017]	0.672	0.049
Industry 7	0.906[.282]	0.038[.325]	0.920	0.032
Industry 8	0.969[.504]	0.032[.364]	0.929	0.032
Industry 9	0.559[.028]	0.305[.052]	0.609	0.261
Industry 10	0.897[.301]	0.028[.554]	0.869	0.026
Industry 11	0.873[.166]	0.043[.120]	0.888	0.043
Industry 12	0.963[.417]	0.007[.932]	0.957	0.007
Government bonds	1.209[.832]	0.446[.016]	0.694	0.253
Corporate bonds	0.571[.100]	0.384[.099]	0.530	0.331
Six-month bill	0.894[.644]	0.294[.417]	0.745	0.208
Average	0.814	0.102	0.810	0.082

Notes: VR1 is the ratio of the variance of the model's predicted return to the variance of expected returns from a linear regression $P(\cdot \mid Z)$ on a set instrumental variables (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 third and fourth columns use an instrument set (Z^0) which excludes the January dummy variable.

The model is estimated with six economic variables: the excess return on the value-weighted NYSE index; the difference in returns for under-Baa rated bonds and government bonds; the first difference of the spread in yields from a 10-year Treasury to a 3-month Treasury—both average yields over the month; the unexpected inflation rate in the not seasonally adjusted consumer price index (from a univariate time-series model; the growth in per capita personal consumption of nondurables (seasonally adjusted) and the real return on a one-month Treasury bill.

All rates of return are in excess of the holding period return on a one month Treasury bill. Decile 1 represents the excess return on the decile of smallest valued firms on the NYSE. Decile 10 represents the excess returns on the largest decile of NYSE stocks. The industry groups are 1 = petroleum, 2 = finance/real estate, 3 = consumer durables, 4 = basic industries, 5 = food/tobacco, 6 = construction, 7 = capital goods, 8 = transportation, 9 = utilities, 10 = textiles/trade, 11 = services and 12 = leisure.

The instrumental variables (Z) are a constant, the lagged excess return on the equally weighted NYSE index, a dummy variable for the month of January, the lagged return for holding a 90-day bill for one month less the return on a 30-day bill, the lagged yield on Moody's Baa rated bonds less the yield on Moody's Aaa rated bonds, the lagged dividend yield on the Standard and Poor's 500 stock index and the return on a one-month Treasury bill.

[a]One tail p-value for the test that the variance ratio equals 1 based on a bootstrapped distribution with 1000 replications.

[b]One tail p-value for the test that the variance ratio equals 0 based on a bootstrapped distribution with 1000 replications.

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 Z_{t-1}. The second decomposition can be expressed for asset i, using notation similar to Equation (5), as follows:

$$\mathrm{var}[P(\beta_i'\lambda \mid Z)] = \{E(\beta_i)'\mathrm{var}[P(\lambda \mid Z)]\, E(\beta_i)\} + \{E(\lambda)'\mathrm{var}[P(\beta_i \mid Z)]\, E(\lambda)\} + \textit{interaction terms}, \qquad (6)$$

where $E(\beta_i)$ and $E(\lambda)$ 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 left-hand panel shows the contributions of the individual economic variables. The variation associated with the expected stock market 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% 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 right-hand panel of Table 8 shows 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.[33] 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 obvious implications for the formulation of time-varying asset pricing models. The evidence suggests that the constant beta assumption made in "latent variables" models (see Ferson, 1990; Gibbons and Ferson, 1985; Hansen and Hodrick, 1983) may be a reasonable

Table 8. Decomposing the Predicted Variation of Monthly Portfolio Returns: 1964–1986:12 (272 Observations)

	Decomposition by Economic Risk Variables							Decomposition by Betas versus 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	0.31	23.22	11.29	1.41	67.80	30.79
Decile 2	51.42	3.90	3.00	5.59	0.25	17.50	18.34	1.20	68.58	30.22
Decile 3	58.59	3.13	2.53	3.39	0.15	14.38	17.83	1.31	75.32	23.37
Decile 4	64.45	1.45	2.01	2.57	0.36	12.06	17.10	0.85	78.71	20.44
Decile 5	69.68	1.81	1.43	1.99	0.16	8.47	16.46	0.46	80.03	19.51
Decile 6	80.05	0.87	1.28	2.00	0.19	8.36	7.25	0.25	85.66	14.09
Decile 7	89.44	0.38	0.61	1.34	0.12	3.62	4.49	0.16	91.62	8.22
Decile 8	85.98	0.38	0.67	1.50	0.14	5.32	6.01	0.25	89.58	10.17
Decile 9	97.13	0.20	0.39	2.65	0.14	1.78	–2.29	0.04	90.87	9.09
Decile 10	105.45	0.10	0.26	0.47	0.06	1.36	–7.70	0.04	111.44	–11.48
Industry 1	150.64	1.91	1.80	67.18	6.80	149.50	–277.83	0.83	146.67	–47.49
Industry 2	112.22	1.32	0.20	7.18	1.80	6.36	–29.08	0.42	101.46	–1.88
Industry 3	87.95	0.89	0.87	4.12	0.73	15.90	–10.42	0.04	93.87	6.09
Industry 4	89.07	0.10	0.22	2.01	1.91	4.09	2.60	0.05	95.80	4.15
Industry 5	82.11	0.96	0.52	5.81	1.50	15.90	–6.80	0.37	89.24	10.39
Industry 6	90.03	1.43	0.66	4.80	0.52	8.44	–5.88	0.33	83.40	16.27
Industry 7	75.32	0.61	1.11	15.26	3.20	13.07	–8.57	3.14	97.24	–0.38

Table 8. (continued)

	Decomposition by Economic Risk Variables							*Decomposition by Betas versus Price of Beta*		
Portfolio	*XVW*	*PREM*	*ΔSLOPE*	*UI*	*CGNON*	*REALTB*	*Interaction Effects*	*Changing Beta*	*Changing Price of Beta*	*Interaction Effects*
Industry 8	75.47	0.67	4.28	6.49	1.56	6.25	5.28	0.66	84.03	15.31
Industry 9	87.61	5.56	4.28	9.41	13.60	8.27	–28.73	1.73	87.66	10.61
Industry 10	65.80	0.27	0.37	7.73	6.37	35.00	–15.54	0.15	80.40	19.45
Industry 11	74.88	0.11	0.37	7.19	0.32	20.71	–3.91	0.75	68.66	30.59
Industry 12	73.12	0.10	1.31	17.07	1.13	43.64	–36.37	0.80	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
Six-month Treasury bill	0.53	39.74	60.74	12.04	5.40	18.76	–37.21	1.19	46.16	52.65

Notes: 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.

All rates of return are in excess of the one-month Treasury bill rate. Decile 1 represents the excess return on the decile of smallest valued firms on the NYSE. Decile 10 represents the excess returns on the largest decile of NYSE stocks. The industry groups are 1 = petroleum, 2 = finance/real estate, 3 = consumer durables, 4 = basic industries, 5 = food/tobacco, 6 = construction, 7 = capital goods, 8 = transportation, 9 = utilities, 10 = textiles/trade, 11 = services, and 12 = leisure.

XVW is the excess return on the value-weighted NYSE index. PREM is the difference in returns for under-Baa rated bonds and government bonds. ΔSLOPE is the first difference of the spread in yields from a 10-year Treasury to a 3-month Treasury—both average yields over the month. UI is the unexpected rate or change in the not seasonally adjusted consumer price index (from a univariate time-series model). CGNON is the growth in per capita personal consumption of nondurables (seasonally adjusted). REALTB is the real return on a one-month Treasury bill.

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, Equation 32), which can be written (dropping time subscripts) as

$$E(r_i) = \beta_{im}(-WJ_{ww}/J_w)\text{var}(dW/W) + \sum_{s=1}^{K}\beta_{is}\,(-J_{ws}/J_w)\text{var}(ds). \tag{7}$$

The risk premium for the market beta is $\gamma_m = (-WJ_{ww}/J_w)\text{var}(dW/W)$, and the price of beta for state variable s is, $\gamma_s = (-J_{ws}/J_w)\text{var}(ds)$, where $J(.)$ is the indirect marginal utility of wealth, W is wealth, and the subscripts on $J(.)$ denote its partial derivatives. The price of beta depends both on risk aversion for the state variable and on the conditional variance of the state variable. Changes in the price of beta are driven by both 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.[34] Portfolios of common stocks are more stable, in terms of relative risk, than individual stocks.[35] 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-squares near 20%. Most of the R-squares exceed 10% and numbers as high as 50–60% 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.[36]

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 you think of the sources of predictable variation in this way, what is 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.

APPENDIX

This appendix evaluates the robustness of empirical results cited in the text to the approach for estimating betas, risk premiums, and standard errors. Five kinds of beta estimates are compared. The first are held nearly constant over the sample period, at the values given by OLS slope coefficients in time-series regressions of the excess returns on the six economic variables described in the paper. The betas are not literally constant because, for each cross-sectional month, we exclude the observation for that month from the time series. We call these the *constant beta* estimates. The *constant beta with Z* estimates are obtained as the regression coefficients of the excess returns on the six economic variables and the vector of predetermined variables, Z_{t-1}, described in the text. We omit the cross-sectional month here as well. The third case is the *5-year rolling* regression betas described in the text. Fourth is a 60-month, rolling beta estimator, where the regressors include the six economic variables and Z_{t-1}. We denote these betas as *5-year rolling, with Z*. Fifth are time-varying, conditional beta estimates which we call the *Davidian–Carroll betas.*

Davidian–Carroll Betas

We estimate conditional betas using methods studied by Davidian and Carroll (1987). Schwert (1989), Hsieh and Miller (1990), and other recent studies adopt similar strategies to estimate conditional variances of stock returns. We extend the approach to estimate conditional betas. We first outline the approach for conditional variances, then describe the extension.

$\sigma^2(R_t \mid Z_{t-1})$ is the variance function of R_t, conditional on a vector of predetermined information Z_{t-1}, which includes a constant. We assume that the conditional

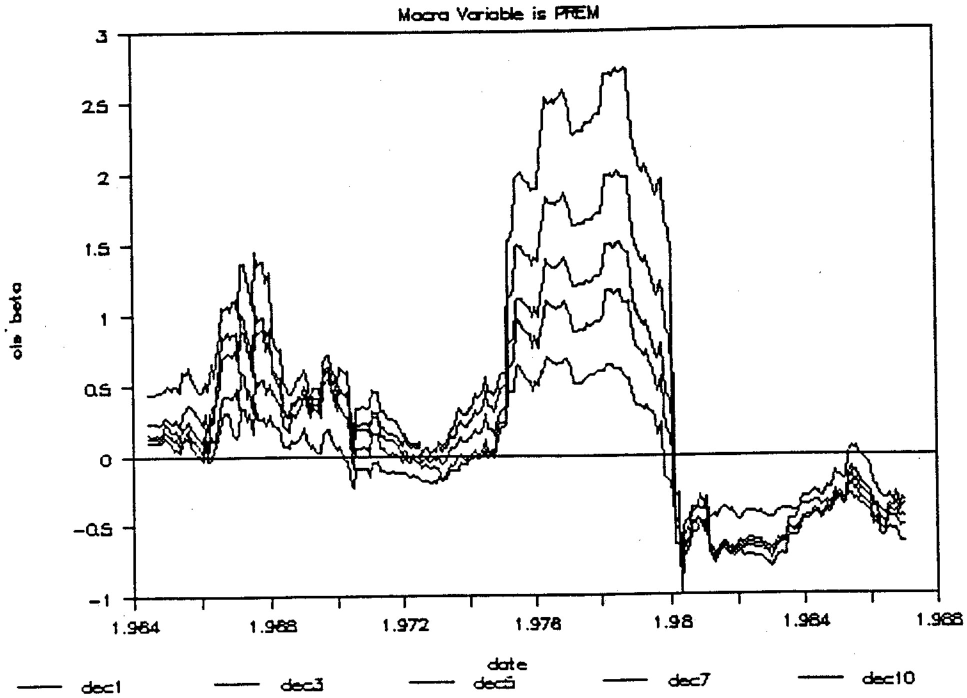

Figure A1. Time series plots of the rolling, five-year beta estimates for selected size portfolios on the economic risk factor "PREM," which is the excess return of a low grade corporate over a long-term government bond. The data are monthly, from 1964:5–1986:12.

mean of R_t is linear in Z_{t-1}. Variance function estimation is based on transformations of the residuals $u_t = R_t - Z_{t-1}\delta$. Davidian and Carroll argue that absolute residuals are a robust choice. They show that the efficiency of variance estimation is monotone in the efficiency of the estimates of the residuals, and they suggest using iterated GLS estimates for the residuals. We adopt a four-stage procedure. In the first stage, we form

$$\hat{u}_t = R_t - Z_{t-1}\hat{\delta},$$

where $\hat{\delta}$ is the OLS coefficient estimate. In stage 2, we form an initial estimate of the conditional standard deviation:

$$|\hat{u}_t| = \sigma(\theta, Z_{t-1}) + e_t.$$

We assume a linear function for $\sigma(.)$, and we obtain the OLS estimate $\hat{\theta}$. A linear function is the simplest model but does not constrain the estimates of the conditional standard deviation to be positive. Negative estimates are not a significant problem in our application. (Of 10,292 point estimates of conditional standard deviations,

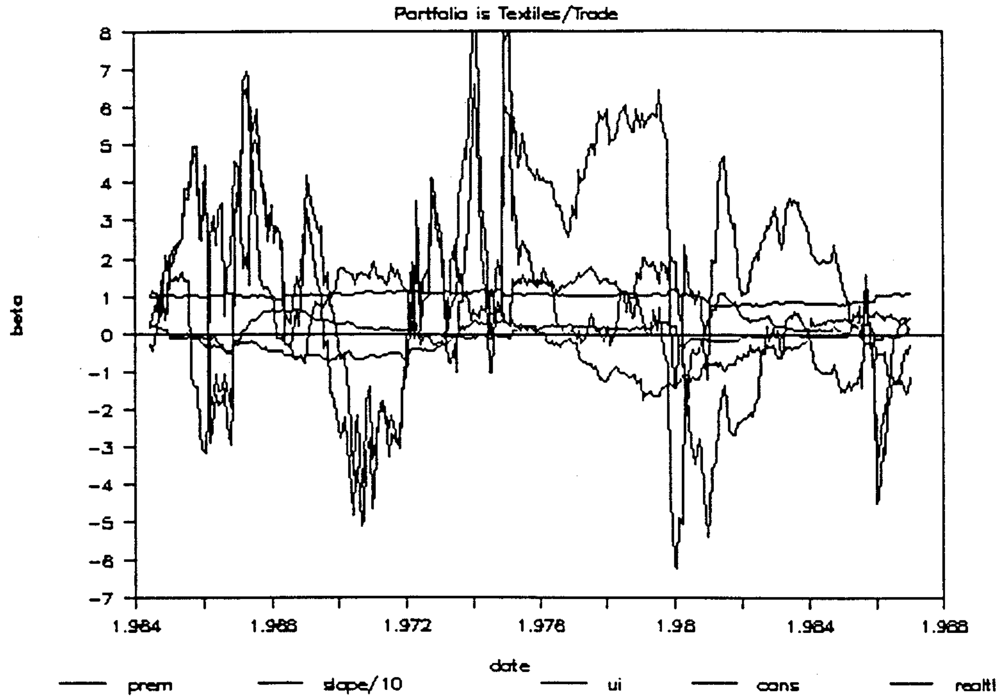

Figure A2. Time series plots of the rolling, five-year multiple regression beta estimates for the textile/trade industry portfolio on five economic risk factors. The data are monthly, from 1964:5–1986:12.

only 19 are less than zero.) We use the fitted $\sigma(\hat{\theta}, Z_{t-1})$ to deflate the observations for a GLS estimator of δ, denoted by δ^*. The regression equation for this step is

$$(R_t/\sigma(\hat{\theta}, Z_{t-1})) = [Z_{t-1}/\sigma(\hat{\theta}, Z_{t-1})]\ \delta^* + U_t^*,$$

In the fourth step, we use the WLS estimate δ^* to generate the final residuals: $u_t^* = R_t - Z_{t-1}\ \delta^*$. We use these residuals to estimate θ^* in

$$|u_t^*| = \sigma(\theta^*, Z_{t-1}) + e_t^*,$$

where $\sigma(\theta^*, Z_{t-1})$ is the fitted conditional standard deviation function. The final estimate of the conditional standard deviation is

$$\sigma^* = \sigma(\theta^*, Z_{t-1})\ \sqrt{(\Pi/2)}.$$

The $\sqrt{(\Pi/2)}$ is a bias adjustment factor which corrects for fact that the mean absolute deviation differs from the standard deviation. The correction is motivated by a normal distribution, for which the standard deviation equals the mean absolute deviation multiplied by $\sqrt{(\Pi/2)}$. [Schwert (1989) and Hsieh and Miller (1990) also use this adjustment.]

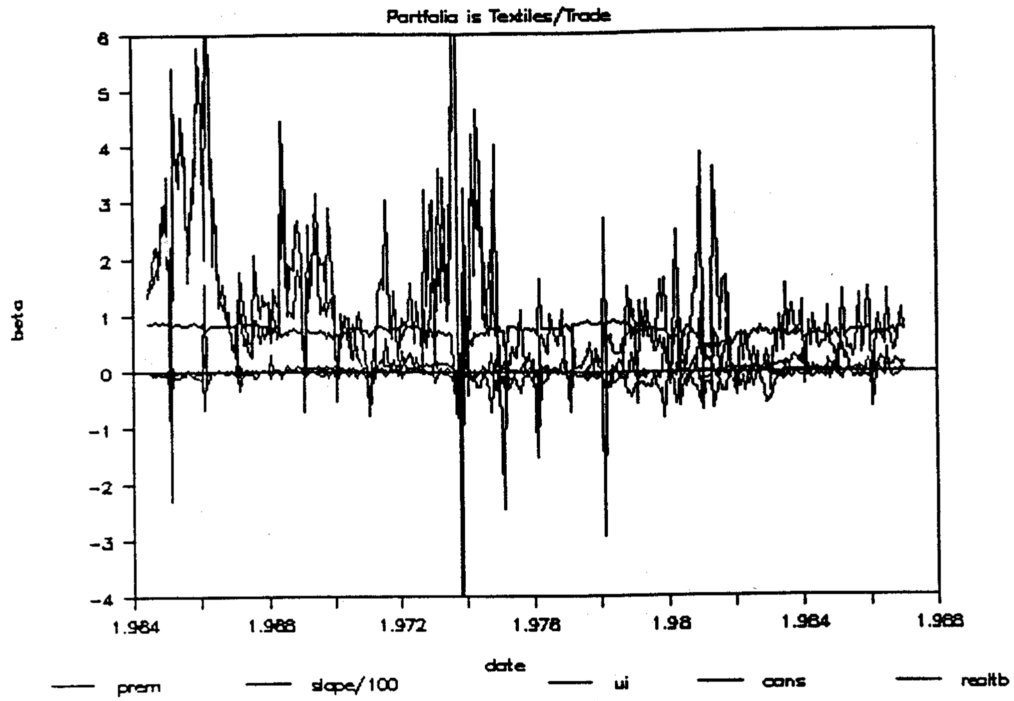

Figure A3. Time series plots of Davidian-carroll conditional beta estimates for the textile/trade industry portfolio on five economic risk factors. The data are monthly, from 1964:5–1986:12.

Summary statistics of the conditional variance estimation appear reasonable. (Tables are available by request.) The average conditional variances are always less than the sample standard deviations of the variables, and the implied variance reduction between the conditional and the unconditional variances is close to that implied by the predictive regressions using the lagged information variables. The sample standard deviations of the conditional variances indicate how much the variances change over time. The standard deviations decline as the market values of the firm-size portfolios increase, suggesting that the volatility of smaller firms is more variable over time. We examine the means and sample standard deviations of the residuals for each variable from the first-step regressions on Z_{t-1}. The residuals are divided by the conditional standard deviation estimates. Such a "studentized" variable should have a mean close to 0.0 and a variance close to 1.0.[37] The means are always close to zero, and only for ΔSLOPE and the six-month Treasury bill return is the sample standard deviation very different from 1.0.

In a multiple-beta model, the relevant conditional betas are the inverse of a conditional variance–covariance matrix, multiplied by a vector of conditional covariances of the assets with the state variables. The diagonal elements of the variance–covariance matrix can be estimated as the square of the conditional

Table A1. Average Correlation of Betas, 1964:5–1986:12 (272 Observations)

Constant Betas	*Constant Betas with Z*	*Five-Year Rolling Betas*	*Five-Year Rolling Betas with Z*	*Davidian–Carroll Betas*
Economic variable is *xvw*				
1.000	0.99906	0.95586	0.95230	0.60265
0.99906	1.0000	0.95718	0.95326	0.60900
0.95586	0.95718	1.0000	0.99386	0.58672
0.95230	0.95326	0.99386	1.0000	0.58475
0.60265	0.60900	0.58672	0.58475	1.0000
Economic variable is *prem*				
1.0000	0.97409	0.84282	0.75054	0.39288
0.97409	1.0000	0.80230	0.76979	0.46702
0.84282	0.80230	1.0000	0.88483	0.29945
0.75054	0.76979	0.88483	1.0000	0.38482
0.39288	0.46702	0.29945	0.38482	1.0000
Economic variable is Δ*slope*				
1.0000	0.66283	0.26433	0.22794	−0.12939
0.66283	1.0000	0.23488	0.25293	−0.033846
0.26433	0.23488	1.0000	0.80765	−0.048515
−0.22794	0.25293	0.80765	1.0000	0.011721
−0.12939	−0.033846	−0.048515	0.011721	1.0000
Economic Variable is *ui*				
1.0000	0.98226	0.024923	0.076422	−0.13124
0.98226	1.0000	0.039327	0.11553	−0.14065
0.024923	0.039327	1.0000	0.61222	0.076758
0.076422	0.11553	0.61222	1.0000	−0.0018312
−0.13124	−0.14065	0.076758	−0.0018312	1.0000
Economic variable is *cgnon*				
1.0000	0.97003	0.35832	0.35033	0.056166
0.37003	1.0000	0.35414	0.38564	0.068094
0.35832	0.35414	1.0000	0.84732	−0.036935
0.35033	0.38564	0.84732	1.0000	−0.029190
0.056166	0.068094	−0.036935	−0.029190	1.0000
Economic variable is *realtb*				
1.0000	0.94679	0.22073	0.22674	0.13487
0.94679	1.0000	0.22964	0.28487	0.13651
0.22073	0.22964	1.0000	0.63023	0.15794
0.22674	0.28487	0.63023	1.0000	0.10821
0.13487	0.13651	0.15794	0.10821	1.0000

Table A2. Summary of Cross-Sectional Regression Results 1964:5–1986:12 (272 Observations)

Type of Beta	*Average Cross-sectional adj. R-square (%)*	*Fama–MacBeth t-statistic for average risk premium*[a] γ_{xvw}	γ_{prem}	$\gamma_{\Delta slope}$	γ_{ui}	γ_{cgnon}	γ_{realtb}
Constant betas	54.6%	1.23	1.90	0.44	−1.07	2.25	1.10
		[1.06]	[1.30]	[0.27]	[−0.66]	[1.38]	[0.68]
		(0.09)[b]	(0.02)	(0.04)	(0.04)	(0.01)	(0.02)
Constant betas with Z	53.5%	1.33	1.70	1.13	−0.69	2.05	1.01
		[1.17]	[1.21]	[0.74]	[−0.45]	[1.32]	[0.65]
		(0.10)	(0.02)	(0.01)	(0.05)	(0.01)	(0.02)
Five-year rolling betas	49.8%	1.07	1.94	2.47	−0.93	2.14	0.84
		[1.04]	[1.75]	[2.04]	[−0.77]	[1.78]	[0.70]
		(0.10)	(0.11)	(0.00)	(0.04)	(0.02)	(0.07)
Five -year rolling betas with Z	46.6%	0.78	2.29	1.38	−0.17	3.15	0.46
		[0.76]	[2.06]	[1.18]	[−0.15]	[2.69]	[0.40]
		(0.13)	(0.02)	(0.04)	(0.05)	(0.09)	(0.06)
Davidian–Carroll betas	44.4%	1.47	1.49	0.68	1.80	0.30	−2.34
		[1.16]	[0.89]	[0.38]	[1.01]	[0.16]	[−1.31]
		(−0.01)	(0.03)	(0.02)	(0.02)	(0.00)	(0.00)

Notes: [a]Shanken asymptotic error corrected t-statistic is shown in square brackets.
[b]Adjusted R-square risk premium regressed on Z is shown in parentheses.

standard deviation estimates, but the off-diagonal terms require a modification of the approach.

To estimate the conditional covariances between two variables i and j, we begin with the residuals u_t* from the third step above. Call the series of +1's and −1's which preserves the sign of the product of the two residuals at each date, $s_{i,j,t}$. In the fourth step, we estimate via OLS the coefficient ψ in the following regression:

$$(\sqrt{|u^*_{it}|})(\sqrt{|u^*_{jt}|})\, s_{i,j,t} = Z_{t-1}\,\psi + \varepsilon_{ij,t}.$$

We then form the fitted conditional covariance as

$$\mathrm{sgn}(Z_{t-1}\,\hat{\psi})*(Z_{t-1}\,\hat{\psi})^2\,(\Pi/2),$$

where $\mathrm{sgn}(x) = x/|x|$.

If the estimators of the conditional means and the conditional covariance are reasonable, the mean of the following quantity should be close to zero:

$$R_{i,t}R_{j,t} - E(R_{i,t}\,|\,Z_{t-1})E(R_{j,t}\,|\,Z_{t-1}) - \mathrm{cov}(R_{i,t};\, R_{j,t}\,|\,Z_{t-1}),$$

where $E(.)$ and cov(.) stand for the conditional mean and covariance estimates. We examine the sample means of this quantity for each of the 6×25 + (6[2]+6)/2 − 6 conditional covariances. The largest sample mean, in absolute value, is 0.0001595.

Table A3. Decomposition of the Predictable Variation of Monthly Portfolio Returns for the Different Beta Models: 1964:5–1986:12 (272 Observations)

Type of Beta:	*Constant Beta*		*Constant Beta with Z*		*Five-Year Rolling No Market Factor*		*Five-Year Rolling with Z*		*Davidian–Carroll*	
Portfolio	*VR1*	*VR2*	*VR1*	*VR2*	*VR1*	*VR2*	*VR1*	*VR2*	*VR1*	*VR2*
Dec 1	58.9	8.6	60.6	8.0	64.5	5.4	65.9	7.0	51.0	10.5
Dec 2	74.8	2.5	77.9	1.7	72.0	3.4	77.0	4.6	65.5	5.5
Dec 3	75.5	2.5	77.4	1.9	70.7	4.6	86.7	1.8	44.9	12.0
Dec 4	88.7	1.6	97.9	1.0	78.2	3.8	97.2	1.8	53.9	9.3
Dec 5	78.0	2.2	81.5	1.5	75.7	5.7	87.2	3.7	59.0	7.6
Dec 6	81.6	2.4	87.6	0.9	81.8	5.7	111.8	3.6	47.3	13.9
Dec 7	86.1	2.0	90.6	1.2	81.1	10.9	103.9	4.5	58.1	13.6
Dec 8	93.5	1.8	100.4	1.1	84.8	11.3	118.4	8.9	61.5	7.1
Dec 9	93.4	1.8	98.6	0.7	75.3	12.5	103.9	8.7	58.9	12.8
Dec 10	97.2	13.5	96.9	10.2	65.5	21.9	101.5	13.4	53.6	15.8
Ind 1	107.0	17.1	100.1	11.7	42.6	29.5	68.0	17.2	46.1	31.6
Ind 2	94.4	3.6	98.1	1.9	63.5	19.1	109.8	14.0	63.1	5.9
Ind 3	74.7	6.0	70.5	8.9	61.3	17.9	86.6	7.3	41.4	21.1
Ind 4	100.7	6.5	114.0	10.1	82.2	20.4	116.9	18.6	64.0	21.6
Ind 5	88.2	2.4	88.4	2.4	86.4	20.7	106.1	18.6	47.7	27.5
Ind 6	69.5	8.4	70.0	8.3	63.1	12.8	79.0	2.6	59.3	15.8
Ind 7	84.7	15.6	83.7	16.1	82.9	11.2	111.1	3.9	37.6	30.0
Ind 8	85.0	4.6	84.7	5.9	96.3	10.1	108.4	4.7	47.9	17.5
Ind 9	69.1	8.8	70.3	8.6	62.6	25.4	87.5	36.2	57.6	32.0
Ind 10	75.4	4.0	74.8	5.1	82.1	13.0	107.5	3.7	25.0	31.8
Ind 11	87.4	3.0	86.4	3.2	83.6	8.1	104.2	5.2	45.9	14.9
Ind 12	85.7	4.2	89.0	2.8	96.6	15.1	108.7	1.1	43.9	29.5
Gov bonds	231.1	70.8	180.1	33.4	70.0	37.0	55.9	26.5	151.0	93.9
Corp bonds	122.2	66.2	110.6	54.0	44.6	36.3	66.0	16.4	114.9	82.9
6 mo bill	177.5	65.2	95.0	15.0	82.8	43.2	157.0	107.1	323.3	150.6
Average	95.2	13.0	91.4	8.6	74.0	16.2	97.0	13.6	68.9	28.6

Without the January Instrument

Dec 1	83.3	1.9	85.4	1.5	77.0	3.5	93.2	1.5	51.5	13.2
Dec 2	83.6	1.1	85.3	0.7	72.2	4.2	93.7	2.9	53.9	8.9
Dec 3	82.3	1.4	82.5	1.3	61.7	6.7	88.6	2.3	41.7	14.0
Dec 4	85.7	2.1	90.9	1.0	67.3	4.7	94.1	2.3	48.2	11.4
Dec 5	83.6	1.1	85.3	1.0	63.4	6.7	89.2	4.2	56.5	8.7
Dec 6	86.8	1.5	91.2	0.5	65.2	5.0	106.2	3.7	43.7	15.3
Dec 7	86.3	2.0	89.4	1.2	63.2	5.7	94.6	2.4	50.8	13.5
Dec 8	96.6	1.2	102.3	1.0	69.0	7.6	113.6	8.5	61.0	7.4
Dec 9	95.4	0.5	100.2	0.3	62.4	7.5	99.4	7.7	57.8	13.1
Dec 10	85.1	2.0	87.6	1.5	56.7	12.5	100.4	12.1	52.7	15.0
Ind 1	86.6	8.7	85.8	6.8	40.1	14.7	70.5	13.6	42.3	32.6
Ind 2	93.0	0.5	98.2	1.3	54.0	12.6	109.3	13.9	62.1	5.6
Ind 3	76.9	2.8	72.6	5.3	51.5	15.6	83.4	7.0	38.5	21.6
Ind 4	102.6	5.3	114.8	10.2	68.7	14.6	113.3	17.9	64.3	16.4
Ind 5	89.5	0.6	89.6	1.7	70.4	12.4	100.9	17.1	45.5	27.7
Ind 6	73.2	4.8	73.4	6.0	50.8	10.9	78.5	2.8	56.7	16.7
Ind 7	82.7	5.4	81.7	5.9	69.8	5.4	109.2	3.6	38.3	29.2
Ind 8	92.4	1.2	92.6	1.7	76.7	6.4	105.0	4.9	44.4	19.2
Ind 9	74.8	4.7	75.6	5.5	54.9	27.2	86.2	39.5	62.7	25.2
Ind 10	77.6	2.8	77.2	3.3	63.8	6.0	102.0	2.4	22.2	32.9
Ind 11	89.6	2.5	87.5	3.1	72.2	5.5	100.3	4.8	11.0	15.4
Ind 12	86.6	3.9	89.0	2.9	75.4	2.7	106.0	0.4	38.2	28.1
Gov bonds	142.1	22.1	133.9	12.8	66.7	40.5	45.0	28.1	142.8	100.0
Corp bonds	80.3	20.8	76.9	17.1	43.6	35.8	66.1	16.4	108.5	75.0
6 mo bill	175.3	64.9	93.5	14.8	63.3	31.2	108.6	71.1	304.8	138.5
Average	91.7	6.6	89.7	4.3	63.2	12.2	94.3	11.6	65.2	28.2

Notes: The ratio of the variance of the model's predicted returns to the variance of expected returns (VR1), from a linear regression $P(\cdot|Z)$ on a set of instrumental variables (Z). VR2 is the ratio of the variance of the part of a return that is not explained by the model to the variance of the expected returns In the second panel, the instrument set (Z^0) excludes the January dummy variable.

The variance ratios are

$$VR1 = \frac{\mathrm{var}[P(\hat{\lambda}\hat{\beta}|Z)]}{\mathrm{var}[P(r|Z)]}, \text{ and } VR2 = \frac{\mathrm{var}[P(r-\hat{\lambda}\hat{\beta}|Z)]}{\mathrm{var}[P(r|Z)]}.$$

But only two cases are greater than half that size. At each date, the vector of *Davidian–Carroll betas* is the inverse of the 6×6 conditional variance–covariance matrix of the economic variables, multiplied by the 6×25 matrix of the conditional covariances of the economic variables with the assets.

Comparison of Beta Estimates

We do not know which of the five estimators provide better estimates of the "true" conditional betas, of course. Figure A1 shows time-series plots of the five-year, rolling regression betas for selected size portfolios, measured against the risk factor PREM. The figure illustrates that both the level and the cross-sectional spread of the rolling betas vary over time. The beta estimates can vary month-to-month quite a bit, even though adjacent beta estimates share 59 months of common data. The amount of variation in the level and the dispersion of the betas provides some feel for why cross-sectional regressions of returns on these betas may produce results which differ in subperiods, and whose coefficients may vary over time.

Figures A2 and A3 compare the time-series plots of the 5-year, rolling betas with the Davidian–Carroll betas for a representative portfolio, the textiles/trade industry. The multiple regression betas for all five risk factors are shown on a single scale. The main point of Figures A2 and A3 is that the two types of beta estimates do not appear similar, which suggests that our experiments using the alternative betas may capture an interesting range of behavior. The figures show that the rolling betas seem to wander much more in the levels and are much smoother than the Davidian–Carroll betas. The Davidian–Carroll betas display more month-to-month variation and show strong seasonal patterns, indicated by the regular spikes in the plots.

In the cross-sectional regressions, the correlation across assets of the beta estimates with the true conditional betas is of primary importance. Table A1 reports sample correlations of the beta estimates. There is one correlation matrix for each of the economic variables. Each matrix contains the average, over the 272 months from 1965:5 to 1986:12, of the sample correlations of the beta across the 25 assets. In the case of the stock market index (*XVW*), the beta estimates are highly correlated. The two constant beta estimates (with and without *Z*) are highly correlated for each of the economic variables. But the correlations indicate that the beta estimates can be quite different. For some of the variables the time-varying beta estimates are nearly uncorrelated. The Davidian–Carroll estimates have the lowest correlation with the other betas.

Sensitivity of the Results to Alternative Betas

Table A2 summarizes results of the cross-sectional regressions using the five beta estimators. The table shows t-ratios for the average risk premiums, the average over the time series of the cross-sectional adjusted R-squares, and the adjusted R-squares from regressing the fitted risk premiums on the predetermined variables, Z_{t-1}. We

Table A4. Decomposition of the Variance of Expected Returns Captured by Multibeta Models 1964:5–1986:12 (272 Observations)

	Type of Beta								
	Five-Year Rolling Betas			*Five-Year Rolling Betas with Z*			*Davidian–Carroll Betas*		
	Variance Component								
Portfolio	$\lambda\beta$	λ	β	$\lambda\beta$	λ	β	$\lambda\beta$	λ	β
Decile 1	8.180	5.546	0.115	8.381	4.595	0.025	2767.87	11.9726	22.3133
Decile 2	6.671	4.575	0.079	6.910	4.330	0.024	1586.52	34.7021	16.6563
Decile 3	5.667	4.268	0.074	6.539	4.110	0.031	339.110	8.80730	3.63042
Decile 4	4.843	3.812	0.041	5.727	4.149	0.016	199.882	5.06631	1.87207
Decile 5	4.296	3.438	0.019	4.712	3.416	0.005	444.648	16.3438	2.14964
Decile 6	3.628	3.108	0.009	4.927	3.549	0.003	79.1623	0.41011	0.90362
Decile 7	3.222	2.952	0.005	4.220	3.635	0.001	249.092	5.88985	0.83636
Decile 8	2.939	2.633	0.007	3.936	3.401	0.003	485.650	2.92169	0.44831
Decile 9	2.446	2.225	0.000	3.014	2.735	0.000	277.878	2.05867	0.22117
Decile 10	1.738	1.936	0.000	2.186	2.459	0.000	10.6905	0.28090	0.10379
Industry 1	1.495	2.197	0.012	1.588	2.263	0.020	1051.13	13.2063	0.62023
Industry 2	2.057	2.088	0.008	2.831	2.589	0.006	416.376	15.1701	0.90229
Industry 3	3.263	3.059	0.001	3.828	3.797	0.005	753.352	24.9516	1.73158
Industry 4	2.383	2.281	0.001	2.903	2.716	0.001	990.960	3.79308	1.82882
Industry 5	1.705	1.521	0.006	2.233	1.921	0.002	301.836	1.00369	1.64933
Industry 6	3.561	2.970	0.011	4.215	3.119	0.016	543.694	30.3788	4.23353
Industry 7	3.160	3.073	0.099	3.877	3.712	0.040	1100.21	26.1580	1.44305
Industry 8	4.826	4.056	0.031	5.403	4.559	0.021	1219.64	42.5732	16.5299
Industry 9	0.908	0.796	0.015	1.418	1.059	0.005	66.1940	2.48871	0.34909
Industry 10	3.347	2.691	0.005	4.012	3.347	0.010	81.3628	0.62105	0.05783
Industry 11	5.101	3.502	0.038	6.075	4.356	0.015	58.9386	3.07605	0.22121
Industry 12	5.013	4.211	0.039	5.660	5.214	0.028	847.795	8.34933	0.93518

Table A4. (continued)

	Type of Beta								
	Five-Year Rolling Betas			*Five-Year Rolling Betas with Z*			*Davidian–Carroll Betas*		
	Variance Component								
Portfolio	$\lambda\beta$	λ	β	$\lambda\beta$	λ	β	$\lambda\beta$	λ	β
Government bond	0.735	0.676	0.012	0.340	0.153	0.005	66.5109	1.73580	0.09208
Corporate bond	0.380	0.227	0.014	0.440	0.075	0.005	548.001	7.28235	0.50121
tb6	0.009	0.004	0.000	0.015	0.006	0.000	0.05619	0.06663	0.00065

Notes: Variance of fitted expected values are multiplied by 10,000. The variance of the expected excess return predicted by the multibeta model, var$\{P(\lambda\beta \mid Z)\}$ is denoted by $\gamma\beta$. The portion of this variance attributed to changing expected risk premiums per unit of beta is $E(\beta)'\text{var}\{P(\lambda \mid Z)\}E(\beta)$ and is denoted by λ. The portion of the predicted variance of the expected return that is attributed to time-varying betas is $E(\lambda)'\text{var}\{P(\beta \mid Z)E(\lambda)$ and is denoted by β. The difference between the total variance of the predicted expected return and these two components is due to interaction effects, which are not shown. These reflect covariation of the expected risk premiums and the betas.

also report t-statistics for the average risk premiums, using the error correction proposed by Shanken (1992).

The most notable differences across the experiments in Table A2 involve the Davidian–Carroll betas. These appear relatively noisy, compared with the other four estimators. There are several symptoms of inefficiency. The Davidian–Carroll betas have the lowest explanatory power in the cross-sectional regressions. The Shanken correction has a relatively large impact on the t-ratios, indicating that the errors-in-the-betas problem is more severe. The premiums associated with UI and REALTB have the opposite sign, compared with the other four beta estimators. Finally, all the adjusted R-squares of the predictive regressions for the fitted risk premiums using the Davidian–Carroll betas are close to zero.

Table A3 summarizes the results of replicating the analysis of variance in Table 7 of the text, using the five beta estimators. The ratios reported for the 5-year rolling betas differ from Table 7 in the text. Here the economic variables exclude the market index XVW. The table shows that most of the predictable variance of the portfolio returns is captured by the model in each case.

Using the 5-year rolling betas with Z, there is a higher frequency of VR1 ratios exceeding 1.0. Since these betas are estimated using the predetermined variables, this probably reflects measurement errors that are correlated with the instruments. Using the Davidian–Carroll betas, more of VR1 ratios are close to 0.5 than with the other betas, but the VR1 ratios are still closer to 1.0 than to 0.0, and VR2 ratios are still closer to 0.0 than to 1.0.

Table A4 examines the robustness of the result that most of the predictable variation in the portfolio returns is associated with changes in the price of beta, as opposed to changing betas. Of course, if the betas are constrained to be constant over time, the model must attribute all the predicted variation to a changing price of beta. Results for the "constant" betas are not shown. The table shows that the component of the predicted variance that is attributed to changing betas is the smaller component in all cases.

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NOTES

1. This is an expanded version of the authors' paper, "The Variation of Economic Risk Premiums," *Journal of Political Economy* 99 (April 1991), 385–415. It includes an appendix and additional material that did not appear in that paper.

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

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

4. See, for example, Sharpe (1977), Cragg and Malkiel (1982), or Shanken (1987). Examples of such models also include Merton (1973), Long (1974), Ross (1976), and Breeden (1979).

5. When the proxies are portfolio returns constructed from the sample of assets, Equation (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.

6. 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.

7. 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.

8. See Shanken (1992) 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 GLS two-stage estimator is consistent and asymptotically efficient.

10. This correction accounts for autocorrelation in the economic variables. The results are in the appendix.

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

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 8 (services industry before September 1960) to a high of 300 (finance/real estate in October 1986). The mean number of firms over the 1959–1986 sample period varies across the industries from 33.6 (services) to 213.7 (basic industries).

13. See Folger, John, and Tipton (1981), Chan et al. (1985), Chen, Roll, and Ross (1986), Sweeney and Warga (1986), Shanken and Weinstein (1987), and Burmeister and McElroy (1988).

14. We use an IMA(1,1) model for the inflation rate:

$$I_t = 2.1E\text{–}06 + I_{t-1} + a_t - 0.724\, a_{t-1};\ \text{adj. } R^2 = 0.54,$$

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(l,l) with an MA parameter equal to 0.93 (standard error 0.03) for the real return. We found little difference between these two models in the accuracy of the inflation forecasts over our sample period.

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

16. 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.

17. we use the one-month bill rate from the CRSP Fama files as an instrument and compute excess returns relative to the Ibbotson and Sinquefield one-month rate to minimize measurement error problems. The CRSP Fama files use the Treasury bill that is the closest to one month to maturity, whereas the Ibbotson and Sinquefield rates are for a bill with at least one month to maturity.

18. 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.

19. Some of the first-order autocorrelations of the instruments are above 0.9 (i.e., JUNK, DIV, and TB1). In the case of DIV, this is expected 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.

20. 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 pricing of the PREM variable. WLS regressions produce slightly smaller average point estimates for the λ's, except for the PREM variable, where the point estimates are slightly larger. But the overall impressions from the two approaches are similar. The Appendix provides further evidence on the sensitivity.

21. 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% after this adjustment. (These are reported in the Appendix.)

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

23. The estimators in the two panels are, of course, different portfolios. In the univariate 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.

24. The 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.

25. These are estimated using the cross-sectional regression coefficients from bivariate models (except the market index, which is from a univariate model), where the market index is the second factor.

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. 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 eleven months.

28. 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."

29. 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. The Appendix provides variance ratios using alternative estimates for the betas. The main results are not sensitive.

30. If the value for x_τ is drawn, we remove u_τ and $u_{\tau-1}$ from the "urn" of the u's for time τ.

31. The experiments show that the expected value of the variance ratio VR1 is less than 1.0 when the model captures 100% of the predictable variation of a return, and the expected value of VR2 is greater than zero. The empirical distributions of the ratios are leptokurtotic, 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.

32. In another experiment, we repeated the analysis using a bias-adjusted cross-sectional coefficient estimator and obtained results similar to those of Table 4. 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, whereas the autocorrelations of the components not related to risk are close to zero.

33. The Appendix shows that this result is robust to alternative beta estimators.

34. 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.

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

36. Chan and Chen (1988) use a model which 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.

37. Because of Jensen's inequality, the mean of the standardized variable is not exactly 1.0, even if the conditional mean function and the conditional standard deviation estimates ar unbiased.

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