Bad Beta, Good Beta

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Abstract

This paper explains the size and value "anomalies" in stock returns using an economically motivated two-beta model. We break the beta of a stock with the market portfolio into two components, one reflecting news about the market's future cash flows and one reflecting news about the market's discount rates. Intertemporal asset pricing theory suggests that the former should have a higher price of risk; thus beta, like cholesterol, comes in "bad" and "good" varieties. Empirically, we find that value stocks and small stocks have considerably higher cash-flow betas than growth stocks and large stocks, and this can explain their higher average returns. The post-1963 negative CAPM alphas of growth stocks are explained by the fact that their betas are predominantly of the good variety.

JEL classification: G12, G14, N22

1 Introduction

According to the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), a stock's risk is summarized by its beta with the market portfolio of all invested wealth. Controlling for beta, no other characteristics of a stock should influence its expected return. It is well known that this model fails to describe the behavior of stock returns since the early 1960's. In particular, small stocks and value stocks have delivered higher average returns than their betas can justify. Adding insult to injury, stocks with high past betas have had average returns no higher than stocks of the same size with low past betas.[2]

This paper argues that returns on the market portfolio have two components. The value of the market portfolio may fall because investors receive bad news about future cash flows; but it may also fall because investors increase the discount rate or cost of capital that they apply to these cash flows. In the first case, wealth decreases and investment opportunities are unchanged, while in the second case, wealth decreases but future investment opportunities improve.

These two components should have different significance for risk-averse long-term investors. They may demand a higher premium to hold assets that covary with the market's cash-flow news than to hold assets that covary with news about the market's discount rates, for poor returns driven by increases in discount rates are partially compensated by improved prospects for future returns. The single beta of the Sharpe-Lintner CAPM should be broken into two different betas: a cash-flow beta and a discount-rate beta. We expect the former to have a higher price of risk than the latter. In fact, an intertemporal asset pricing model suggests that the price of risk for the discount-rate beta should equal the variance of the market return, while the price of risk for the cash-flow beta should be γ times higher, where γ is the coefficient of relative risk aversion of a representative investor.

An intuitive way to summarize our story is to say that beta, like cholesterol, has a "bad" variety and a "good" variety. The expected return on a stock is determined not by its overall beta with the market, but by its bad cash-flow beta and its good

[2] Seminal early references include Banz (1981) and Reinganum (1981) for the size effect, and Graham and Dodd (1934), Basu (1977, 1983), Ball (1978), and Rosenberg, Reid, and Lanstein (1985) for the value effect. Fama and French (1992) give an influential treatment of both effects within an integrated framework and show that sorting stocks on past market betas generates little variation in average returns.

discount-rate beta. Of course, the good beta is good not in absolute terms, but in relation to the other type of beta.

We test these ideas by fitting a two-beta model to historical monthly returns on stock portfolios sorted by size, book-to-market ratios, and market betas. We consider not only a sample period since 1963 that has been the subject of much recent research, but also an earlier sample period 1929-1963 using the data of Davis, Fama, and French (2000). In the modern period, 1963:7-2001:12, we find that the two-beta model greatly improves the poor performance of the standard CAPM. The main reason for this is that growth stocks, with low average returns, have high betas with the market portfolio; but their high betas are predominantly good betas, with low risk prices. Value stocks, with high average returns, have higher bad betas than growth stocks do. In the early period, 1929:1-1963:6, we find that value stocks have higher CAPM betas and proportionately higher bad betas than growth stocks, so the single-beta CAPM adequately explains the data.

The intertemporal CAPM is also successful in explaining the size effect. Over both subperiods, small stocks outperform large stocks by approximately 3% per annum. In the early period, this performance differential is justified by the moderately higher cash-flow and discount-rate betas of small stocks relative to large stocks. In the modern period, small and large stocks have approximately equal cash-flow betas. However, small stocks have much higher discount-rate betas than large stocks in the post-1963 sample. Even though the premium on discount-rate beta is low, the magnitude of the beta spread is sufficient to explain most of the size premium.

Our two-beta model also casts light on why portfolios sorted on past CAPM betas show a spread in average returns in the early sample period but not in the modern period. In the early sample period, a sort on CAPM beta induces a strong post-ranking spread in cash-flow betas, and this spread carries an economically significant premium, as the theory predicts. In the modern period, however, sorting on past CAPM betas produces a spread only in good discount-rate betas but no spread in bad cash-flow betas. Since the good beta carries only a low premium, the almost flat relation between average returns and the CAPM beta estimated from these portfolios in the modern period is no puzzle to the two-beta model.

In developing and testing the two-beta model, we draw on a great deal of related literature. The idea that the market's return can be attributed to cash-flow and discount-rate news is not novel. Campbell and Shiller (1988a) developed a loglinear approximate framework in which to study the effects of changing cash-flow and discount-rate forecasts on stock prices. Campbell (1991) used this framework and a vector autoregressive (VAR) model to decompose market returns into cash-flow news and discount-rate news. Empirically, he found that discount-rate news was far from negligible; in postwar US data, for example, his VAR system explained most stock return volatility as the result of discount-rate news. Campbell and Mei (1993) used a similar approach to decompose the market betas of industry and size portfolios into cash-flow betas and discount-rate betas, but they did not estimate separate risk prices for these betas.

The insight that long-term investors care about shocks to investment opportunities is due to Merton (1973). Campbell (1993) solved a discrete-time empirical version of Merton's model, assuming that a representative investor has the recursive preferences proposed by Epstein and Zin (1989, 1991). The solution is exact in the limit of continuous time if the representative investor has elasticity of intertemporal substitution equal to one, and is otherwise a loglinear approximation. Campbell wrote the solution in the form of a K-factor model, where the first factor is the market return and the other factors are shocks to variables that predict the market return. Campbell (1996) tested this model on industry portfolios, but found that the innovation to discount rates was highly correlated with the innovation to the market itself; thus his multi-beta model was hard to distinguish empirically from the CAPM. Li (1997), Hodrick, Ng, and Sengmueller (1999), Lynch (1999), Chen (2000), Brennan, Wang, and Xia (2001), Ng (2002), and Guo (2002) have also explored the empirical implications of Merton's model.

Brennan, Wang, and Xia (2001), the paper that is closest to ours in its focus, estimates a structural model of time-varying investment opportunities in which both the riskless interest rate and the Sharpe ratio on the market portfolio follow continuous-time AR(1) processes. Brennan et al. estimate the parameters of their model using both bond market and stock market data, and explore the model's implications for the value and size effects in US data since 1953. They have some success in explaining these effects if they estimate risk prices from stock market data rather than bond market data. They do not consider prewar US data or stock portfolios sorted by past CAPM betas.

Recently, several authors have found that high returns to growth stocks, particularly small growth stocks, seem to predict low returns on the aggregate stock market. Eleswarapu and Reinganum (2001) use lagged 3-year returns on an equal-weighted index of growth stocks, while Brennan, Wang, and Xia (2001) use the difference between the log book-to-market ratios of small growth stocks and small value stocks to predict the aggregate market. These findings suggest that growth and value stocks might have different betas with discount-rate news and thus might have average returns that are inconsistent with the CAPM even in an efficient market.

It is natural to ask why high returns on small growth stocks should predict low returns on the stock market as a whole. This is a particularly important question since time-series regressions of aggregate stock returns on arbitrary predictor variables can easily produce meaningless data-mined results. One possibility is that small growth stocks generate cash flows in the more distant future and therefore their prices are more sensitive to changes in discount rates, just as coupon bonds with a high duration are more sensitive to interest-rate movements than are bonds with a low duration (Cornell 1999). Another possibility is that small growth companies are particularly dependent on external financing and thus are sensitive to equity market and broader financial conditions (Ng, Engle, and Rothschild 1992, Perez-Quiros and Timmermann 2000). A third possibility is that episodes of irrational investor optimism (Shiller 2000) have a particularly powerful effect on small growth stocks.

Our finding that value stocks have higher cash-flow betas than growth stocks is consistent with the empirical results of Cohen, Polk, and Vuolteenaho (2002a). Cohen et al. measure cash-flow betas by regressing the multi-year return on equity (ROE) of value and growth stocks on the market's multi-year ROE. They find that value stocks have higher ROE betas than growth stocks. There is also evidence that value stock returns are correlated with shocks to GDP-growth forecasts (Liew and Vassalou 2000, Vassalou 2002). The sensitivity of value stocks' cash-flow fundamentals to economy-wide cash-flow fundamentals plays a key role in our two-beta model's ability to explain the value premium.

The changes in the risk characteristics of value and growth stocks that we identify by comparing the periods before and after 1963 are consistent with recent research by Franzoni (2002). Franzoni points out that the market betas of value stocks and small stocks have declined over time relative to the market betas of growth stocks and large stocks. We extend his research by exploring time changes in the two components of market beta, the cash-flow beta and the discount-rate beta.

There are numerous competing explanations for the size and value effects. At the most basic level the Arbitrage Pricing Theory (APT) of Ross (1976) allows any pervasive source of common variation to be a priced risk factor. Fama and French

(1993) showed that small stocks and value stocks tend to move together as groups, and introduced an influential three-factor model, including a market factor, size factor, and value factor, to describe the size and value effects in average returns. As Fama and French recognize, ultimately this falls short of a satisfactory explanation because the APT is silent about what determines factor risk prices; in a pure APT model the size premium and the value premium could just as easily be zero or negative.

Jagannathan and Wang (1996) point out that the CAPM might hold conditionally, but fail unconditionally. If some stocks have high market betas at times when the market risk premium is high, then these stocks should have higher average returns than are explained by their unconditional market betas. Lettau and Ludvigson (2001) argue that value stocks satisfy these conditions.

Adrian and Franzoni (2002) and Lewellen and Shanken (2002) consider the possibility that investors do not know the risk characteristics of stocks but must learn about them over time. Adrian and Franzoni, for example, suggest that investors tended to overestimate the market betas of value and small stocks as these betas trended downwards during the 20th Century. This led investors to demand higher average returns for such stocks than are justified by their average market risks.

Roll (1977) emphasized that tests of the CAPM are misspecified if one cannot measure the market portfolio correctly. While Stambaugh (1982) and Shanken (1987) found that CAPM tests are insensitive to the inclusion of other financial assets, more recent research has stressed the importance of human wealth whose return can be proxied by revisions in expected future labor income (Campbell 1996, Jagannathan and Wang 1996, Lettau and Ludvigson 2001).

Finally, the value effect has been interpreted in behavioral terms. Lakonishok, Shleifer, and Vishny (1994), for example, argue that investors irrationally extrapolate past earnings growth and thus overvalue companies that have performed well in the past. These companies have low book-to-market ratios and subsequently underperform once their earnings growth disappoints investors. Supporting evidence is provided by La Porta (1996), who shows that high long-term earnings forecasts of stock market analysts predict low stock returns while low forecasts predict high returns, and by La Porta et al. (1997), who show that the underperformance of stocks with low book-to-market ratios is concentrated on earnings announcement dates.

In this paper we do not consider any of these alternative stories. We assume that unconditional betas are adequate proxies for conditional betas, we use a value-weight index of common stocks as a proxy for the market portfolio, and we test an orthodox asset pricing model with a rational representative investor who knows the parameters of the model. Our purpose is to clarify the extent to which deviations from the CAPM's cross-sectional predictions can be rationalized by Merton's (1973) intertemporal hedging considerations that are relevant for long-term investors. This exercise should be of interest even if one believes that investor irrationality has an important effect on stock prices, because even in this case one should want to know how a rational investor will perceive the risks of small stocks and value stocks.

The organization of the paper is as follows. In Section 2, we estimate two components of the return on the aggregate stock market, one caused by cash-flow shocks and the other by discount-rate shocks. In Section 3, we use these components to estimate cash-flow and discount-rate betas for portfolios sorted on firm characteristics and risk loadings. In Section 4, we lay out the intertemporal asset pricing theory that justifies different risk premia for bad cash-flow beta and good discount-rate beta. We also show that the returns to small and value stocks can largely be explained by allowing different risk premia for these two different betas. Section 5 concludes.

2 How cash-flow and discount-rate news move the market

A simple present-value formula points to two reasons why stock prices may change. Either expected cash flows change, discount rates change, or both. In this section, we empirically estimate these two components of unexpected return for a value-weighted stock market index. Consistent with findings of Campbell (1991), the fitted values suggest that over our sample period (1929:1-2001:12) discount-rate news causes much more variation in monthly stock returns than cash-flow news.

2.1 Return-decomposition framework

Campbell and Shiller (1988a) developed a loglinear approximate present-value relation that allows for time-varying discount rates. They did this by approximating the definition of log return on a dividend-paying asset, $r_{t+1} \equiv \log(P_{t+1} + D_{t+1}) - \log(P_t)$, around the mean log dividend-price ratio, $(\overline{d_t - p_t})$, using a first-order Taylor expansion. Above, P denotes price, D dividend, and lower-case letters log transforms. The resulting approximation is $r_{t+1} \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t$,where ρ and k are parameters of linearization defined by $\rho \equiv 1/\big(1 + \exp(\overline{d_t - p_t})\big)$ and $k \equiv -\log(\rho) - (1-\rho)\log(1/\rho - 1)$. When the dividend-price ratio is constant, then $\rho = P/(P+D)$, the ratio of the ex-dividend to the cum-dividend stock price. The approximation here replaces the log sum of price and dividend with a weighted average of log price and log dividend, where the weights are determined by the average relative magnitudes of these two variables.

Solving forward iteratively, imposing the "no-infinite-bubbles" terminal condition that $\lim_{j\to\infty} \rho^j (d_{t+j} - p_{t+j}) = 0$, taking expectations, and subtracting the current dividend, one gets

$$p_t - d_t = \frac{k}{1-\rho} + \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j [\Delta d_{t+1+j} - r_{t+1+j}] \;, \tag{1}$$

where Δd denotes log dividend growth. This equation says that the log price-dividend ratio is high when dividends are expected to grow rapidly, or when stock returns are expected to be low. The equation should be thought of as an accounting identity rather than a behavioral model; it has been obtained merely by approximating an identity, solving forward subject to a terminal condition, and taking expectations. Intuitively, if the stock price is high today, then from the definition of the return and the terminal condition that the dividend-price ratio is non-explosive, there must either be high dividends or low stock returns in the future. Investors must then expect some combination of high dividends and low stock returns if their expectations are to be consistent with the observed price.

While Campbell and Shiller (1988a) constrain the discount coefficient ρ to values determined by the average log dividend yield, ρ has other possible interpretations as well. Campbell (1993, 1996) links ρ to the average consumption-wealth ratio. In effect, the latter interpretation can be seen as a slightly modified version of the former. Consider a mutual fund that reinvests dividends and a mutual-fund investor who finances her consumption by redeeming a fraction of her mutual-fund shares every year. Effectively, the investor's consumption is now a dividend paid by the fund and the investor's wealth (the value of her remaining mutual fund shares) is now the ex-dividend price of the fund. Thus, we can use (1) to describe a portfolio strategy as well as an underlying asset and let the average consumption-wealth ratio generated by the strategy determine the discount coefficient ρ, provided that the consumption-wealth ratio implied by the strategy does not behave explosively.

Campbell (1991) extended the loglinear present-value approach to obtain a decomposition of returns. Substituting (1) into the approximate return equation gives

$$\begin{aligned} r_{t+1} - \mathrm{E}_t\, r_{t+1} &= (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \qquad (2) \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned}$$

where N_{CF} denotes news about future cash flows (i.e., dividends or consumption), and N_{DR} denotes news about future discount rates (i.e., expected returns). This equation says that unexpected stock returns must be associated with changes in expectations of future cash flows or discount rates. An increase in expected future cash flows is associated with a capital gain today, while an increase in discount rates is associated with a capital loss today. The reason is that with a given dividend stream, higher future returns can only be generated by future price appreciation from a lower current price.

These return components can also be interpreted as permanent and transitory shocks to wealth. Returns generated by cash-flow news are never reversed subsequently, whereas returns generated by discount-rate news are offset by lower returns in the future. From this perspective it should not be surprising that conservative long-term investors are more averse to cash-flow risk than to discount-rate risk.

2.2 Implementation with a VAR model

We follow Campbell (1991) and estimate the cash-flow-news and discount-rate-news series using a vector autoregressive (VAR) model. This VAR methodology first estimates the terms $\mathrm{E}_t\, r_{t+1}$ and $(\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ and then uses r_{t+1} and equation (2) to back out the cash-flow news. This practice has an important advantage – one does not necessarily have to understand the short-run dynamics of dividends. Understanding the dynamics of expected returns is enough.

We assume that the data are generated by a first-order VAR model

$$z_{t+1} = a + \Gamma z_t + u_{t+1}, \tag{3}$$

where z_{t+1} is a m-by-1 state vector with r_{t+1} as its first element, a and Γ are m-by-1 vector and m-by-m matrix of constant parameters, and u_{t+1} an i.i.d. m-by-1 vector of shocks. Of course, this formulation also allows for higher-order VAR models via a simple redefinition of the state vector to include lagged values.

Provided that the process in equation (3) generates the data, $t+1$ cash-flow and discount-rate news are linear functions of the $t+1$ shock vector:

$$\begin{aligned} N_{CF,t+1} &= (e1' + e1'\lambda)\, u_{t+1} \\ N_{DR,t+1} &= e1'\lambda u_{t+1}. \end{aligned} \tag{4}$$

The VAR shocks are mapped to news by λ, defined as $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$. $e1'\lambda$ captures the long-run significance of each individual VAR shock to discount-rate expectations. The greater the absolute value of a variable's coefficient in the return prediction equation (the top row of Γ), the greater the weight the variable receives in the discount-rate-news formula. More persistent variables should also receive more weight, which is captured by the term $(I - \rho\Gamma)^{-1}$.

2.3 VAR data

To operationalize the VAR approach, we need to specify the variables to be included in the state vector. We opt for a parsimonious model with the following four state variables. First, the excess log return on the market (r_M^e) is the difference between the log return on the Center for Research in Securities Prices (CRSP) value-weighted stock index (r_M) and the log risk-free rate. The risk-free-rate data are constructed by CRSP from Treasury bills with approximately three month maturity.

Second, the term yield spread (TY) is provided by Global Financial Data and is computed as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes, in percentage points.

Third, the price-earnings ratio (PE) is from Shiller (2000), constructed as the price of the S&P 500 index divided by a ten-year trailing moving average of aggregate earnings of companies in the S&P 500 index. Following Graham and Dodd (1934), Campbell and Shiller (1988b, 1998) advocate averaging earnings over several years to avoid temporary spikes in the price-earnings ratio caused by cyclical declines in earnings. We avoid any interpolation of earnings in order to ensure that all components of the time-t price-earnings ratio are contemporaneously observable by time t. The ratio is log transformed.

Fourth, the small-stock value spread (VS) is constructed from the data made available by Professor Kenneth French on his web site.[3] The portfolios, which are constructed at the end of each June, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The BE/ME breakpoints are the 30th and 70th NYSE percentiles.

At the end of June of year t, we construct the small-stock value spread as the difference between the $\log(BE/ME)$ of the small high-book-to-market portfolio and the $\log(BE/ME)$ of the small low-book-to-market portfolio, where BE and ME are measured at the end of December of year $t-1$. For months from July to May, the small-stock value spread is constructed by adding the cumulative log return (from the previous June) on the small low-book-to-market portfolio to, and subtracting the cumulative log return on the small high-book-to-market portfolio from, the end-of-June small-stock value spread.

Our small-stock value spread is similar to variables constructed by Asness, Fried-

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

man, Krail, and Liew (2000), Cohen, Polk, and Vuolteenaho (2002b), and Brennan, Wang, and Xia (2001). Asness et al. use a number of different scaled-price variables to construct their measures, and also incorporate analysts' earnings forecasts into their model. Cohen et al. use the entire CRSP universe instead of small-stock portfolios to construct their value-spread variable. Brennan et al.'s small-stock value-spread variable is equal to ours at the end of June of each year, but the intra-year values differ because Brennan et al. interpolate the intra-year values of BE using year t and year $t+1$ BE values. We do not follow their procedure because we wish to avoid using any future variables that might cause spurious forecastability of stock returns.

These state-variable series span the period 1928:12-2001:12. Table 1 shows descriptive statistics and Figure 1 the time-series evolution of the state-variable series. The variables in Figure 1 are demeaned and normalized by the sample standard deviation. Monthly excess log returns on the market are marked with solid circles. The figure shows that returns were especially volatile during the Great Depression – in fact, some of the Great-Depression data points are not shown since they fall outside the +/- four standard deviation range shown in the figure.

The black solid line plots the evolution of PE, the log ratio of price to ten-year moving average of earnings. Our sample period begins only months before the stock market crash of 1929. This event is clearly visible from the graph in which the log price-earnings drops by an extraordinary five sample standard deviations from 1929 to 1932. Another striking episode is the 1983-1999 bull market, during which the price-earnings ratio increases by four sample standard deviations.

While the price-earnings ratio and its historical time-series behavior are well known, the history of the small-stock value spread is perhaps less so. Recall that our value-spread variable is the difference between value stocks' log book-to-market ratio and growth stocks' log book-to-market ratio. Similar to figures shown by Cohen, Polk, and Vuolteenaho (2002b) and Brennan, Wang, and Xia (2001), the post-war variation in VS appears positively correlated with the price-earnings ratio, high overall stock prices coinciding with especially high prices for growth stocks. The pre-war data appear quite different from the post-war data, however. For the first two decades of our sample, the value spread is negatively correlated with the market's price-earnings ratio. The correlation between VS and PE is -.48 in the period 1928:12–1963:6, and .57 in the period 1963:7–2001:12. If most value stocks were highly levered and financially distressed during and after the Great Depression, it makes sense that their

Table 1: Descriptive statistics of the VAR state variables

The table shows the descriptive statistics of the VAR state variables estimated from the full sample period 1928:12-2001:12, 877 monthly data points. r^e_M is the excess log return on the CRSP value-weight index. TY is the term yield spread in percentage points, measured as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes. PE is the log ratio of S&P 500's price to S&P 500's ten-year moving average of earnings. VS is the small-stock value-spread, the difference in the log book-to-market ratios of small value and small growth stocks. The small value and small growth portfolios are two of the six elementary portfolios constructed by Davis, Fama, and French (2000). "Stdev." denotes standard deviation and "Autocorr." the first-order autocorrelation of the series.

Variable	Mean	Median	Stdev.	Min	Max	Autocorr.
r^e_M	.004	.009	.056	-.344	.322	.108
TY	.629	.550	.643	-1.350	2.720	.906
PE	2.868	2.852	.374	1.501	3.891	.992
VS	2.653	1.522	.374	1.192	2.713	.992
Correlations	$r^e_{M,t+1}$	TY_{t+1}	PE_{t+1}	VS_{t+1}		
$r^e_{M,t+1}$	1	.071	-.006	-.030		
TY_{t+1}	.071	1	-.253	.423		
PE_{t+1}	-.006	-.253	1	-.320		
VS_{t+1}	-.030	.423	-.320	1		
$r^e_{M,t}$	.103	.065	.070	-.031		
TY_t	.070	.906	-.248	.420		
PE_t	-.090	-.263	.992	-.318		
VS_t	-.025	.425	-.322	.992		

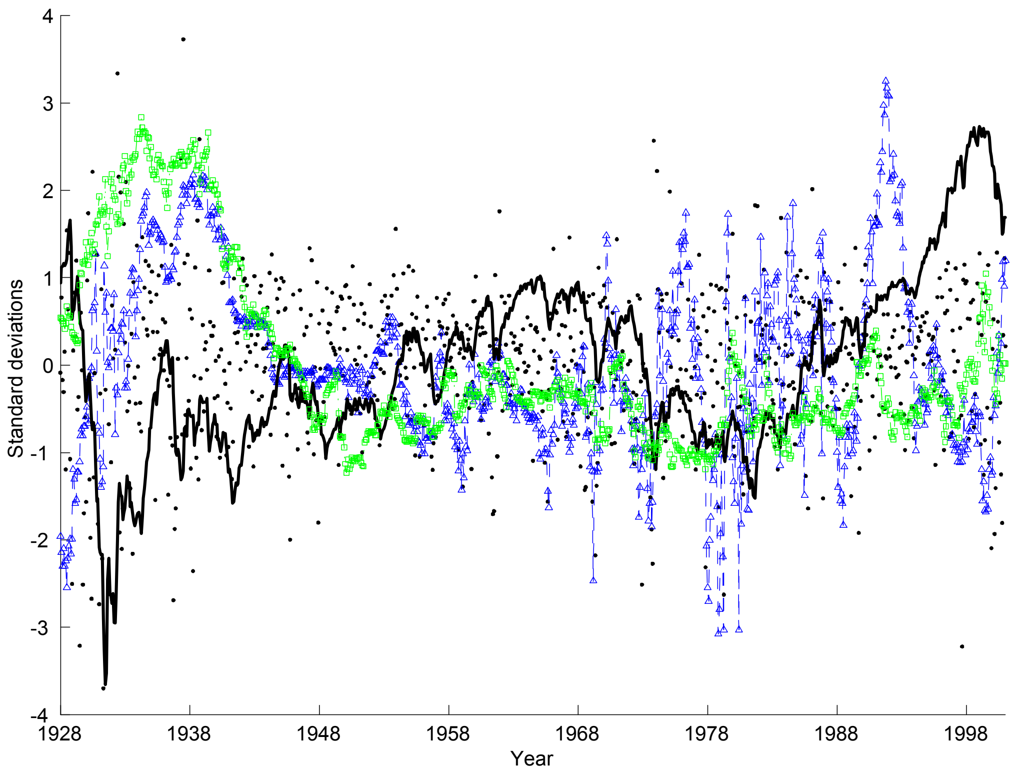

Figure 1: Time-series evolution of the VAR state variables.

This figure plots the time-series of four state variables: (1) The excess log return on the CRSP value-weight portfolio, marked with dots; (2) the log ratio of price to a ten-year moving average of earnings, marked with a solid line; (3) the small-stock value spread, marked with line and squares; and (4) the term yield spread, marked with dashed line and triangles. All variables are demeaned and normalized by their sample standard deviations. The sample period is 1928:12-2001:12.

values were especially sensitive to changes in overall economic prospects, including the cost of capital. In the post-war period, however, most value stocks were probably stable businesses with relatively low financial leverage, no growth options, and thus probably little dependence on external equity-market financing. We will return to this changing sensitivity of value and growth stocks to various economy-wide shocks in Section 3.

The term yield spread (TY) is a variable that is known to track the business cycle, as discussed by Fama and French (1989). The term yield spread is very volatile during the Great Depression and again in the 1970's. It also tracks the value spread closely, with a correlation of .42 over the full sample as shown in Table 1. This positive correlation between the term yield spread and the value spread is natural: Long bonds and growth stocks have effectively higher maturities than short bonds and value stocks. Thus, any shock to the long end of the term structure of interest rates is likely to move long bonds and growth stocks, and therefore TY and VS, in the same direction. Cornell (1999) emphasizes this interpretation of growth stocks as high-duration assets.

2.4 VAR parameter estimates

Table 2 reports parameter estimates for the VAR model. Each row of the table corresponds to a different equation of the model. The first five columns report coefficients on the five explanatory variables: a constant, and lags of the excess market return, term yield spread, price-earnings ratio, and small-stock value spread. OLS standard errors are reported in square brackets below the coefficients. For comparison, we also report in parentheses standard errors from a bootstrap exercise. Finally, we report the R^2 and F statistics for each regression. The bottom of the table reports the correlation matrix of the equation residuals, with standard deviations of each residual on the diagonal.

The first row of Table 2 shows that all four of our VAR state variables have some ability to predict excess returns on the aggregate stock market. Market returns display a modest degree of momentum; the coefficient on the lagged excess market return is .094 with a standard error of .034. The term yield spread positively predicts the market return, consistent with the findings of Keim and Stambaugh (1986), Campbell (1987), and Fama and French (1989). The smoothed price-earnings ratio negatively predicts the return, consistent with Campbell and Shiller (1988b, 1998)

Table 2: VAR parameter estimates

The table shows the OLS parameter estimates for a first-order VAR model including a constant, the log excess market return (r^e_M), term yield spread (TY), price-earnings ratio (PE), and small-stock value spread (VS). Each set of three rows corresponds to a different dependent variable. The first five columns report coefficients on the five explanatory variables, and the remaining columns show R^2 and F statistics. OLS standard errors are in square brackets and bootstrap standard errors in parentheses. Bootstrap standard errors are computed from 2500 simulated realizations. The table also reports the correlation matrix of the shocks with shock standard deviations on the diagonal, labeled "corr/std." Sample period for the dependent variables is 1929:1-2001:12, 876 monthly data points.

	constant	$r^e_{M,t}$	TY_t	PE_t	VS_t	R^2 %	F
$r^e_{M,t+1}$	.062	.094	.006	-.014	-.013	2.57	5.34
	[.020]	[.033]	[.003]	[.005]	[.006]		
	(.026)	(.034)	(.003)	(.007)	(.008)		
TY_{t+1}	.046	.046	.879	-.036	.082	82.41	$1.02\times_{10}{}^3$
	[.097]	[.165]	[.016]	[.026]	[.028]		
	(.012)	(.170)	(.017)	(.031)	(.036)		
PE_{t+1}	.019	.519	.002	.994	-.003	99.06	$2.29\times_{10}{}^4$
	[.013]	[.022]	[.002]	[.004]	[.004]		
	(.017)	(.022)	(.002)	(.004)	(.005)		
VS_{t+1}	.014	-.005	.002	.000	.991	98.40	$1.34\times_{10}{}^4$
	[.017]	[.029]	[.003]	[.005]	[.005]		
	(.024)	(.028)	(.003)	(.006)	(.008)		

corr/std	$r^e_{M,t+1}$	TY_{t+1}	PE_{t+1}	VS_{t+1}
$r^e_{M,t+1}$	.055	.018	.777	-.052
	(.003)	(.048)	(.018)	(.052)
TY_{t+1}	.018	.268	.018	-.012
	(.048)	(.013)	(.039)	(.034)
PE_{t+1}	.777	.018	.036	-.086
	(.018)	(.039)	(.002)	(.045)
VS_{t+1}	-.052	-.012	-.086	.047
	(.052)	(.034)	(.045)	(.003)

and related work using the aggregate dividend-price ratio (Rozeff 1984, Campbell and Shiller 1988a, and Fama and French 1988, 1989). The small-stock value spread negatively predicts the return, consistent with Eleswarapu and Reinganum (2002) and Brennan, Wang, and Xia (2001). Overall, the R^2 of the return forecasting equation is about 2.6%, which is a reasonable number for a monthly model.

The remaining rows of Table 2 summarize the dynamics of the explanatory variables. The term spread is approximately an AR(1) process with an autoregressive coefficient of .88, but the lagged small-stock value spread also has some ability to predict the term spread. This should not be surprising given the contemporaneous correlation of these two variables illustrated in Figure 1. The price-earnings ratio is highly persistent, with a root very close to unity, but it is also predicted by the lagged market return. This predictability may reflect short-term momentum in stock returns, but it may also reflect the fact that the recent history of returns is correlated with earnings news that is not yet reflected in our lagged earnings measure. Finally, the small-stock value spread is also a highly persistent AR(1) process.

The persistence of the VAR explanatory variables raises some difficult statistical issues. It is well known that estimates of persistent AR(1) coefficients are biased downwards in finite samples, and that this causes bias in the estimates of predictive regressions for returns if return innovations are highly correlated with innovations in predictor variables (Stambaugh 1999). There is an active debate about the effect of this on the strength of the evidence for return predictability (Ang and Bekaert 2001, Campbell and Yogo 2002, Lewellen 2002, Torous, Valkanov, and Yan 2001).

For our sample and VAR specification, the four predictive variables in the return prediction equation are jointly significant at a better than 5% level. Our unreported experiments show that the joint significance of the return-prediction equation at 5% level survives bootstrapping excess returns as return shocks and simulating from a system estimated under the null with various bias adjustments. However, the statistical significance of the one-period return-prediction equation does not guarantee that our news terms are not materially affected by the above-mentioned small-sample bias.

As a simple way to assess the impact of this bias, we have generated 2500 artificial data series using the estimated VAR coefficients and have reestimated the VAR system 2500 times. The difference between the average coefficient estimates in the artificial data and the original VAR estimates is a simple measure of finite-sample bias. We find that there is some bias in the VAR coefficients, but it does not have a large effect on our estimates of cash-flow and discount-rate news. The reason is that the bias causes some overstatement of short-term return predictability (the $e1'\rho\Gamma$ component of $e1'\lambda$) but an understatement of the persistence of the VAR, and thus an understatement of the long-term impact of predictability [the $(I-\rho\Gamma)^{-1}$ component of $e1'\lambda$]. These two effects work against each other. The one variable that is moderately affected by bias is the value spread, whose role in predicting returns is biased downwards. Since this bias works against us in explaining the average returns on value and growth stocks, we do not attempt to correct it. Instead we use the estimated VAR as a reasonable representation of the data and ask what it implies for cross-sectional asset pricing puzzles.

Table 3 summarizes the behavior of the implied cash-flow news and discount-rate news components of the market return. The top panel shows that discount-rate news has a standard deviation of about 5% per month, much larger than the 2.5% standard deviation of cash-flow news. This is consistent with the finding of Campbell (1991) that discount-rate news is the dominant component of the market return. The table also shows that the two components of return are almost uncorrelated with one another. This finding differs from Campbell (1991) and particularly Campbell (1996); it results from our use of a richer forecasting model that includes the value spread as well as the aggregate price-earnings ratio.

Table 3 also reports the correlations of each state variable innovation with the estimated news terms, and the coefficients $(e1' + e1'\lambda)$ and $e1'\lambda$ that map innovations to cash-flow and discount-rate news. Innovations to returns and the price-earnings ratio are highly negatively correlated with discount-rate news, reflecting the mean reversion in stock prices that is implied by our VAR system. Market return innovations are weakly positively correlated with cash-flow news, indicating that some part of a market rise is typically justified by underlying improvements in expected future cash flows. Innovations to the price-earnings ratio, however, are weakly negatively correlated with cash-flow news, suggesting that price increases relative to earnings are not usually justified by improvements in future earnings growth.

We set $\rho = .95^{1/12}$ in Table 3 and use the same value throughout the paper. Recall that ρ can be related to either the average dividend yield or the average consumption wealth ratio, as discussed on page 7. An annualized ρ of .95 corresponds to an average dividend-price or consumption-wealth ratio of -2.94 (in logs) or 5.2% (in levels), where wealth is measured after subtracting consumption. We picked the value .95 because approximately 5% consumption of the total wealth per year seems reasonable for a

Table 3: Cash-flow and discount-rate news for the market portfolio

The table shows the properties of cash-flow news (N_{CF}) and discount-rate news (N_{DR}) implied by the VAR model of Table 2. The upper-left section of the table shows the covariance matrix of the news terms. The upper-right section shows the correlation matrix of the news terms with standard deviations on the diagonal. The lower-left section shows the correlation of shocks to individual state variables with the news terms. The lower right section shows the functions $(e1' + e1'\lambda, e1'\lambda)$ that map the state-variable shocks to cash-flow and discount-rate news. We define $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$, where Γ is the estimated VAR transition matrix from Table 2 and ρ is set to .95. r_M^e is the excess log return on the CRSP value-weight index. TY is the term yield spread. PE is the log ratio of S&P 500's price to S&P 500's ten-year moving average of earnings. VS is the small-stock value-spread, the difference in log book-to-markets of value and growth stocks.

News covariance	N_{CF}	N_{DR}	News corr/std	N_{CF}	N_{DR}
N_{CF}	.00064	.00015	N_{CF}	.0252	.114
	(.00022)	(.00037)		(.004)	(.232)
N_{DR}	.00015	.00267	N_{DR}	.114	.0517
	(.00037)	(.00070)		(.232)	(.007)
Shock correlations	N_{CF}	N_{DR}	**Functions**	N_{CF}	N_{DR}
r_M^e shock	.352	-.890	r_M^e shock	.602	-.398
	(.224)	(.036)		(.060)	(.060)
TY shock	.128	.042	TY shock	.011	.011
	(.134)	(.081)		(.013)	(.013)
PE shock	-.204	-.925	PE shock	-.883	-.883
	(.238)	(.039)		(.104)	(.104)
VS shock	-.493	-.186	VS shock	-.283	-.283
	(.243)	(.152)		(.160)	(.160)

long-term investor. To alleviate any possible concerns about this choice, we will assess the sensitivity of our asset-pricing results to changes in ρ in a future draft.

As a robustness check, we have estimated the VAR over subsamples before and after 1963. The coefficients that map state variable innovations to cash-flow and discount-rate news are fairly stable, with no changes in sign. Also, the value spread has greater predictive power in the first subsample than in the second. This is reassuring, since it indicates that the coefficient on this variable is not just fitting the last few years of the sample during which exceptionally high prices for growth stocks preceded a market decline. Given the stability of the VAR point estimates in the two subsamples and the unfortunate statistical fact that the coefficients of our monthly return-prediction regressions are estimated imprecisely (a problem that is magnified in shorter subsamples), we proceed to use the full-sample VAR-coefficient estimates in the remainder of the paper.

3 Measuring cash-flow and discount-rate betas

We have shown that market returns contain two components, both of which display substantial volatility and which are not highly correlated with one another. This raises the possibility that different types of stocks may have different betas with the two components of the market. In this section we measure cash-flow betas and discount-rate betas separately. We define the cash-flow beta as

$$\beta_{i,CF} \equiv \frac{\operatorname{Cov}\left(r_{i,t}, N_{CF,t}\right)}{\operatorname{Var}\left(r^e_{M,t} - E_{t-1} r^e_{M,t}\right)} \tag{5}$$

and the discount-rate beta as

$$\beta_{i,DR} \equiv \frac{\operatorname{Cov}\left(r_{i,t}, -N_{DR,t}\right)}{\operatorname{Var}\left(r^e_{M,t} - E_{t-1} r^e_{M,t}\right)}. \tag{6}$$

Note that the discount-rate beta is defined as the covariance of an asset's return with *good* news about the stock market in form of *lower-than-expected* discount rates, and that each beta divides by the total variance of unexpected market returns, not the variance of cash-flow news or discount-rate news separately. This implies that the cash-flow beta and the discount-rate beta add up to the total market beta,

$$\beta_{i,M} = \beta_{i,CF} + \beta_{i,DR}. \tag{7}$$

Our estimates show that there is interesting variation across assets and across time in the two components of the market beta.

3.1 Test-asset data

Our main set of test assets is a set of 25 ME and BE/ME portfolios, available from Professor Kenneth French's web site. The portfolios, which are constructed at the end of each June, are the intersections of five portfolios formed on size (ME) and five portfolios formed on book-to-market equity (BE/ME). BE/ME for June of year t is the book equity for the last fiscal year end in the calendar year $t-1$ divided by ME for December of $t-1$. The size and BE/ME breakpoints are NYSE quintiles. On a few occasions, no firms are allocated to some of the portfolios. In those cases, we use the return on the portfolio with the same size and the closest BE/ME.

The 25 ME and BE/ME portfolios were originally constructed by Davis, Fama, and French (2000) using three databases. The first of these, the CRSP monthly stock file, contains monthly prices, shares outstanding, dividends, and returns for NYSE, AMEX, and NASDAQ stocks. The second database, the COMPUSTAT annual research file, contains the relevant accounting information for most publicly traded U.S. stocks. The COMPUSTAT accounting information is supplemented by the third database, Moody's book equity information hand collected by Davis et al.

We also consider 20 portfolios sorted on past risk loadings with VAR state variables (excluding the price-smoothed earnings ratio PE, since changes in PE are so highly collinear with market returns). These risk-sorted portfolios are constructed as follows. First, we run a loading-estimation regression for each stock in the CRSP database:

$$\sum_{j=1}^{3} r_{i,t+j} = b_0 + b_{r_M} \sum_{j=1}^{3} r_{M,t+j} + b_{VS}(VS_{t+3} - VS_t) + b_{TY}(TY_{t+3} - TY_t) + \varepsilon_{i,t+3}, \quad (8)$$

where $r_{i,t}$ is the log stock return on stock i for month t. The regression (8) is reestimated from a rolling 36-month window of overlapping observations for each stock at the end of each month. Since these regressions are estimated from stock-level instead of portfolio-level data, we use a quarterly data frequency to minimize the impact of infrequent trading.

Our objective is to create a set of portfolios that have as large a spread as possible in their betas with the market and with innovations in the VAR state variables. To accomplish this, each month we perform a two-dimensional sequential sort on market beta and another state-variable beta, producing a set of ten portfolios for each state variable. First, we form two groups by sorting stocks on $\widehat{b}_{VS}$. Then, we further sort stocks in both groups to five portfolios on $\widehat{b}_{r_M}$ and record returns on these ten value-weight portfolios. To ensure that the average returns on these portfolio strategies are not influenced by various market-microstructure issues plaguing the smallest stocks, we exclude the smallest (lowest ME) five percent of stocks of each cross-section and lag the estimated risk loadings by a month in our sorts. We construct another set of ten portfolios in a similar fashion by sorting on $\widehat{b}_{TY}$ and $\widehat{b}_{r_M}$. We later refer to these 20 portfolio return series that span the time period 1929:1-2001:12 as the risk-sorted portfolios.

3.2 Empirical estimates of cash-flow and discount-rate betas

We estimate the cash-flow and discount-rate betas using the fitted values of the market's cash-flow and discount-rate news. Specifically, we use the following beta estimators:

$$\widehat{\beta}_{i,CF} = \frac{\widehat{\text{Cov}}\left(r_{i,t}, \widehat{N}_{CF,t}\right)}{\widehat{\text{Var}}\left(\widehat{N}_{CF,t} - \widehat{N}_{DR,t}\right)} + \frac{\widehat{\text{Cov}}\left(r_{i,t}, \widehat{N}_{CF,t-1}\right)}{\widehat{\text{Var}}\left(\widehat{N}_{CF,t} - \widehat{N}_{DR,t}\right)} \tag{9}$$

$$\widehat{\beta}_{i,DR} = \frac{\widehat{\text{Cov}}\left(r_{i,t}, -\widehat{N}_{DR,t}\right)}{\widehat{\text{Var}}\left(\widehat{N}_{CF,t} - \widehat{N}_{DR,t}\right)} + \frac{\widehat{\text{Cov}}\left(r_{i,t}, -\widehat{N}_{DR,t-1}\right)}{\widehat{\text{Var}}\left(\widehat{N}_{CF,t} - \widehat{N}_{DR,t}\right)} \tag{10}$$

Above, $\widehat{\text{Cov}}$ and $\widehat{\text{Var}}$ denote sample covariance and variance. $\widehat{N}_{CF,t}$ and $\widehat{N}_{DR,t}$ are the estimated cash-flow and expected-return news from the VAR model of Tables 2 and 3.

These beta estimators deviate from the usual regression-coefficient estimator in two respects. First, we include one lag of the market's news terms in the numerator. Adding a lag is motivated by the possibility that, especially during the early years of our sample period, not all stocks in our test-asset portfolios were traded frequently and synchronously. If some portfolio returns are contaminated by stale prices, market return and news terms may spuriously appear to lead the portfolio returns, as noted by Scholes and Williams (1977) and Dimson (1979). In addition, Lo and MacKinlay (1990) show that the transaction prices of individual stocks tend to react in part to movements in the overall market with a lag, and the smaller the company, the greater is the lagged price reaction. McQueen, Pinegar, and Thorley (1996) and Peterson and Sanger (1995) show that these effects exist even in relatively low-frequency data (i.e., those sampled monthly). These problems are alleviated by the inclusion of the lag term.

Second, as in (5) and (6), we normalize the covariances in (9) and (10) by $\widehat{\text{Var}}(\widehat{N}_{CF,t} - \widehat{N}_{DR,t})$ or, equivalently by the sample variance of the (unexpected) market return, $\widehat{\text{Var}}\left(r^e_{M,t} - E_{t-1}r^e_{M,t}\right)$. Under the maintained assumptions, $\widehat{\beta}_{i,M} = \widehat{\beta}_{i,CF} + \widehat{\beta}_{i,DR}$ is equal to the portfolio i's Scholes-Williams (1977) beta on unexpected market return. It is also equal to the so-called "sum beta" employed by Ibbotson Associates, which is the sum of multiple regression coefficients of a portfolio's return

Table 4: Cash-flow and discount-rate betas for the 25 ME and BE/ME portfolios

The table shows the estimates of cash-flow betas ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$) for Davis, Fama, and French's (2000) 25 size- and book-to-market-sorted portfolios. The betas are estimated using equations (5) and (6) and the news terms extracted from the VAR model in Table 2. Bootstrap standard errors, constructed from 2500 simulated samples, are in parentheses. "Growth" denotes the lowest BE/ME, "value" the highest BE/ME, "small" the lowest ME, and "large" the highest ME stocks. "Diff." is the difference between the extreme cells of the particular row or column. Estimates are for the full 1929:1-2001:12 period, and data are monthly.

$\widehat{\beta}_{CF}$	Growth		2		3		4		Value		Diff.	
Small	.36	(.21)	.31	(.19)	.29	(.18)	.30	(.17)	.36	(.19)	.00	(.07)
2	.20	(.16)	.25	(.16)	.26	(.15)	.29	(.16)	.33	(.19)	.13	(.09)
3	.20	(.16)	.22	(.15)	.24	(.15)	.27	(.15)	.35	(.19)	.14	(.09)
4	.14	(.14)	.20	(.14)	.24	(.14)	.26	(.16)	.36	(.20)	.23	(.11)
Large	.14	(.12)	.15	(.12)	.21	(.13)	.25	(.16)	.30	(.19)	.16	(.09)
Diff.	-.22	(.10)	-.16	(.07)	-.08	(.06)	-.05	(.04)	-.07	(.04)		
$\widehat{\beta}_{DR}$	Growth		2		3		4		Value		Diff.	
Small	1.45	(.24)	1.43	(.21)	1.27	(.20)	1.22	(.19)	1.22	(.21)	-.22	(.07)
2	1.22	(.17)	1.17	(.17)	1.08	(.16)	1.08	(.17)	1.17	(.20)	-.05	(.09)
3	1.23	(.17)	1.04	(.15)	1.03	(.15)	.97	(.16)	1.15	(.20)	-.08	(.09)
4	1.01	(.14)	1.00	(.14)	.94	(.15)	.96	(.16)	1.19	(.21)	.17	(.11)
Large	.92	(.13)	.84	(.13)	.83	(.13)	.91	(.16)	1.00	(.19)	.08	(.09)
Diff.	-.52	(.13)	-.59	(.12)	-.44	(.09)	-.31	(.07)	-.21	(.08)		

on contemporaneous and lagged unexpected market returns.[4]

[4]Scholes and Williams (1977) include an additional lead term, which captures the possibility that the market return itself is contaminated by stale prices. Under the maintained assumption that our news terms are unforecastable, the population value of this term is zero.

The Scholes-Williams beta formula also includes a normalization. The sum of the three regression coefficients is divided by one plus twice the market's autocorrelation. Since the first-order autocorrelation of our news series is zero unser the maintained assumptions, this normalization factor is identically one.

"Sum beta" uses multiple regression coefficients instead of simple regression coefficients. Under the maintained assumption that the news terms are unforecastable, the explanatory variables in the multiple regression are uncorrelated, and thus the multiple regression coefficients are equal to simple regression coefficients.

Table 4 shows the estimated cash-flow and discount-rate betas for the 25 size and book-to-market portfolios over the entire 1929:1-2001:12 sample. The portfolios are organized in a square matrix with growth stocks at the left, value stocks at the right, small stocks at the top, and large stocks at the bottom. At the right edge of the matrix we report the differences between the extreme growth and extreme value portfolios in each size group; along the bottom of the matrix we report the differences between the extreme small and extreme large portfolios in each BE/ME category.

Over the full sample period and controlling for size, value stocks generally have higher cash-flow betas than growth stocks. The exception is the set of five smallest portfolios at the top of the table. The smallest growth portfolio is particularly risky and has a cash-flow beta equal to that of the smallest value portfolio. This small growth portfolio is well known to present a particular challenge to asset pricing models, for example the three-factor model of Fama and French (1993) which does not fit this portfolio well. Excluding the smallest growth portfolio, the cash-flow betas tend to increase as we move to the right even in the top row of the table.

Discount-rate betas show a contrasting pattern. In the three smallest size groups, discount-rate betas are higher for growth stocks than for value stocks; in the two largest size groups, they are slightly bigger for value stocks. If we add cash-flow and discount-rate betas to obtain market beta, we find that a higher fraction of the market beta is cash-flow beta for value stocks than for growth stocks. This pattern in the cash-flow-to-CAPM-beta ratio is monotonic as a function of book-to-market within each size group, except for the extreme small-growth portfolio.

Table 5 shows the cash-flow and discount-rate betas for the risk-sorted portfolios. Cash-flow betas are high for stocks with low past sensitivity to the value spread, and also for stocks that have had high market betas in the past. Discount-rate betas are high for stocks with high past sensitivity to the term spread, and particularly for stocks that have had high market betas in the past. Thus, over the full sample, sorting stocks by their value-spread sensitivity induces a spread in cash-flow betas but not in discount-rate betas; sorting stocks by their term-spread sensitivity induces a spread in discount-rate betas but not in cash-flow betas; and sorting stocks by their past market betas induces a modest spread in cash-flow betas and a large spread in discount-rate betas.

Table 5: Cash-flow and discount-rate betas for the risk-sorted portfolios

The table shows the estimates of cash-flow betas ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$) for the 20 risk-sorted portfolios. The betas are estimated using equations (5) and (6) and the news terms extracted from the VAR model in Table 2. The risk-sorted portfolios are constructed as follows. First, we run a loading-estimation regression (8) for each stock in the CRSP database. The regression is reestimated from a rolling 36-month window of overlapping observations for each stock at the end of each month. Each month we perform a two-dimensional sequential sort on market beta and a state variable beta, producing a set of ten portfolios for each state variable. First, we form two groups by sorting stocks on past sensitivity to changes in the small-stock value spread ($\widehat{b}_{VS}$). Then, we further sort stocks in both groups to five portfolios on past sensitivity to market return ($\widehat{b}_{r_M}$) and record returns on these ten value-weight portfolios. We exclude the smallest (lowest ME) five percent of stocks of each cross-section and lag the estimated risk loadings by a month in our sorts. We construct another set of ten portfolios in a similar fashion by sorting on past sensitivity to changes in term yield spread ($\widehat{b}_{TY}$) and $\widehat{b}_{r_M}$. Bootstrap standard errors are in parentheses. Estimates are for the full 1929:1-2001:12 period, and data are monthly.

$\widehat{\beta}_{CF}$	Lo $\widehat{b}_{r_M}$		2		3		4		Hi $\widehat{b}_{r_M}$		Diff.	
Lo $\widehat{b}_{VS}$	.16	(.11)	.19	(.13)	.23	(.15)	.27	(.18)	.34	(.22)	.17	(.11)
Hi $\widehat{b}_{VS}$	.12	(.09)	.14	(.11)	.19	(.14)	.20	(.16)	.26	(.19)	.14	(.10)
Lo $\widehat{b}_{TY}$	.13	(.10)	.15	(.12)	.20	(.15)	.23	(.17)	.28	(.20)	.15	(.10)
Hi $\widehat{b}_{TY}$	.14	(.10)	.16	(.11)	.20	(.13)	.24	(.16)	.29	(.29)	.15	(.10)
$\widehat{\beta}_{DR}$	Lo $\widehat{b}_{r_M}$		2		3		4		Hi $\widehat{b}_{r_M}$		Diff.	
Lo $\widehat{b}_{VS}$	.68	(.11)	.84	(.13)	.98	(.16)	1.17	(.18)	1.44	(.22)	.76	(.12)
Hi $\widehat{b}_{VS}$	.65	(.10)	.79	(.12)	1.00	(.14)	1.16	(.16)	1.40	(.20)	.74	(.11)
Lo $\widehat{b}_{TY}$	.73	(.11)	.85	(.12)	1.02	(.15)	1.19	(.18)	1.46	(.21)	.72	(.11)
Hi $\widehat{b}_{TY}$	.63	(.10)	.77	(.12)	.89	(.14)	1.10	(.16)	1.36	(.20)	.72	(.11)

3.3 Value and size aren't what they used to be

The full-sample results in Tables 4 and 5 conceal quite different beta patterns in the first subsample and the second subsample. Table 6 shows the estimated betas for the 25 size- and book-to-market-sorted portfolios for the two subperiods 1929:1-1963:6 and 1963:7-2001:12. We choose to split the sample at 1963:7, because that is when COMPUSTAT data become reliable and because most of the evidence on the book-to-market anomaly is obtained from the post-1963:7 period. Unlike the thoroughly mined second subsample, the first subsample is relatively untouched and presents an opportunity for an out-of-sample test.

In the first subsample, value stocks have both higher cash-flow and higher discount-rate betas. With the exception of the smallest growth portfolio, value stocks are the riskiest assets in both dimensions in this period. An equal-weighted average of the extreme value stocks across size quintiles has a cash-flow beta .16 higher than an equal-weighted average of the extreme growth stocks. The difference in estimated discount-rate betas is .22 in the same direction. Similar to value stocks, small stocks have higher cash-flow betas and discount-rate betas than large stocks in this sample (by .18 and .36 respectively, for an equal-weighted average of the smallest stocks across value quintiles relative to an equal-weighted average of the largest stocks). In summary, value and small stocks were unambiguously riskier than growth and large stocks over the 1929:1-1963:6 period.

The patterns are completely different in the post-1963 period. In this subsample, value stocks have slightly higher cash-flow betas than growth stocks, but much lower discount-rate betas. The difference in cash-flow betas between the average across extreme value portfolios and the average across extreme growth portfolios is a modest and statistically insignificant .09. What is remarkable is that the pattern of discount-rate betas reverses in the modern period, so that growth stocks have significantly higher discount-rate betas than value stocks. The difference is economically large (.45) and statistically significant. Recall that cash-flow and discount-rate betas sum up to the CAPM beta; thus growth stocks have higher market betas in the modern subperiod, but their betas are disproportionately of the "good" discount-rate variety rather than the "bad" cash-flow variety.

Figure 2 shows the time-series evolution of the cash-flow and discount-rate risk in more detail. We first estimate a time-series of cash-flow and discount-rate betas for the 25 ME and BE/ME portfolios using a 120-month window. The series in Figure

Table 6: Subperiod betas for the 25 ME and BE/ME portfolios

The table shows the estimates of cash-flow betas ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$) for Davis, Fama, and French's (2000) 25 size- and book-to-market-sorted portfolios for the two subperiods (1929:1-1963:6 and 1963:7-2001:12). Footnotes of Table 4 apply.

1929:1-1963:6

$\widehat{\beta}_{CF}$	Growth		2		3		4		Value		Diff.	
Small	.53	(.28)	.46	(.24)	.40	(.23)	.42	(.22)	.49	(.25)	-.04	(.07)
2	.30	(.18)	.34	(.29)	.36	(.18)	.38	(.20)	.45	(.24)	.16	(.08)
3	.30	(.18)	.28	(.27)	.31	(.18)	.35	(.19)	.47	(.24)	.18	(.08)
4	.20	(.14)	.26	(.26)	.31	(.17)	.35	(.19)	.50	(.26)	.30	(.12)
Large	.20	(.14)	.19	(.14)	.28	(.16)	.33	(.20)	.40	(.24)	.19	(.11)
Diff.	-.33	(.15)	-.26	(.11)	-.12	(.09)	-.09	(.05)	-.10	(.05)		

$\widehat{\beta}_{DR}$	Growth		2		3		4		Value		Diff.	
Small	1.32	(.31)	1.46	(.28)	1.32	(.26)	1.27	(.25)	1.27	(.28)	-.06	(.15)
2	1.04	(.20)	1.15	(.20)	1.09	(.20)	1.25	(.22)	1.25	(.26)	.21	(.11)
3	1.13	(.19)	1.01	(.18)	1.08	(.18)	1.05	(.20)	1.27	(.25)	.14	(.09)
4	.87	(.15)	.97	(.17)	.97	(.18)	1.06	(.20)	1.36	(.27)	.49	(.14)
Large	.88	(.14)	.82	(.15)	.87	(.16)	1.06	(.20)	1.18	(.25)	.31	(.13)
Diff.	-.45	(.20)	-.64	(.17)	-.43	(.13)	-.21	(.09)	-.08	(.10)		

1963:7-2001:12

$\widehat{\beta}_{CF}$	Growth		2		3		4		Value		Diff.	
Small	.06	(.24)	.07	(.19)	.09	(.16)	.09	(.14)	.13	(.14)	.07	(.13)
2	.04	(.24)	.08	(.18)	.10	(.14)	.11	(.13)	.12	(.14)	.09	(.13)
3	.03	(.22)	.09	(.15)	.11	(.13)	.12	(.12)	.13	(.13)	.09	(.14)
4	.03	(.20)	.10	(.15)	.11	(.12)	.11	(.11)	.13	(.12)	.10	(.12)
Large	.03	(.14)	.08	(.12)	.09	(.11)	.11	(.10)	.11	(.10)	.09	(.09)
Diff.	-.03	(.11)	.02	(.10)	-.01	(.08)	.02	(.08)	-.01	(.07)		

$\widehat{\beta}_{DR}$	Growth		2		3		4		Value		Diff.	
Small	1.66	(.26)	1.37	(.21)	1.18	(.17)	1.12	(.16)	1.12	(.15)	-.54	(.14)
2	1.54	(.25)	1.22	(.19)	1.07	(.16)	.96	(.14)	1.03	(.15)	-.52	(.14)
3	1.41	(.23)	1.11	(.16)	.95	(.14)	.82	(.13)	.94	(.14)	-.47	(.15)
4	1.27	(.21)	1.05	(.15)	.89	(.13)	.79	(.13)	.87	(.14)	-.41	(.14)
Large	1.00	(.15)	.87	(.13)	.74	(.12)	.63	(.11)	.68	(.11)	-.33	(.11)
Diff.	-.66	(.14)	-.50	(.13)	-.44	(.10)	-.49	(.11)	-.44	(.10)		

2 are constructed from the estimated betas as follows: The value-minus-growth series, denoted by a solid line and triangles in the figure, is the equal-weight average of the five extreme value (high BE/ME) portfolios' betas less the equal-weight average of the five extreme growth (low BE/ME) portfolios' betas. The small-minus-big series, denoted by a solid line, is constructed as the equal-weight average of the five extreme small (low ME) portfolios' betas less the equal-weight average of the five extreme large (high ME) portfolios' betas. The top panel shows the cash-flow betas and the bottom panel discount-rate betas. The dates on the horizontal axes are centered with respect to the estimation window.

Two trends stand out in the top panel of Figure 2. First, for the majority of our sample period, the higher-frequency movements in cash-flow betas of value-minus-growth and small-minus-big appear correlated, the small stocks' cash-flow betas possibly leading the value stocks' cash-flow betas. This pattern is strongly reversed in the 1990's, during which the cash-flow betas of small stocks clearly diverge from those of the value stocks. Second, over the entire period, the cash-flow betas of small stocks have drifted down relative to those of large stocks, while the cash-flow betas of value stocks remain considerably higher than the growth stocks (.15 higher at the beginning of the sample and .17 higher at the end).

The bottom panel of Figure 2 shows the time-series evolution of discount-rate betas. The first obvious trend in the figure is the steady and large decline in the discount-rate betas of value stocks relative to those of growth stocks. Over the full sample, the value-minus-growth beta declines from .31 to -.86. There is no similar trend for the discount-rate beta of small-minus-big, for which the time series begins at .37 and ends at .62. As for cash-flow betas, the discount-rate betas of value-minus-growth and small-minus-big strongly diverge during the nineties.

What economic forces have caused these trends in betas? We suspect that the changing characteristics of value and growth stocks and small and large stocks are related to these patterns in sensitivities. The early part of our sample is dominated by the Great Depression and its aftermath. Perhaps in the 1930's value stocks were fallen angels with a large debt load accumulated during the Great Depression. The higher leverage of value stocks relative to that of growth stocks could explain both the higher cash-flow and expected-return betas of value stocks from 1930-1950. In general, low leverage and strong overall position of a company may lead to a low cash-flow beta, and high leverage and weak position to a high cash-flow beta.

We also hypothesize that future investment opportunities, long duration of cash

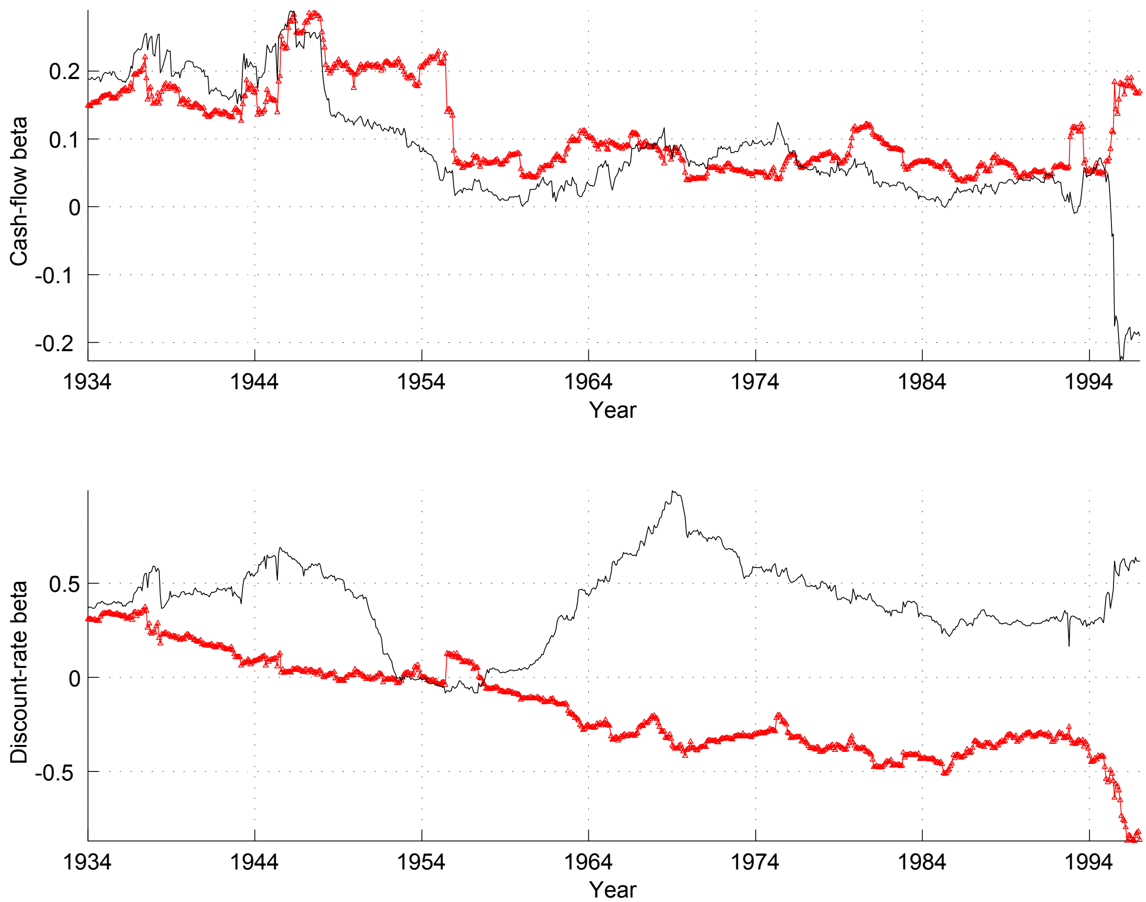

Figure 2: Time-series evolution of cash-flow and discount-rate betas of value-minus-growth and small-minus-big.

First, we estimate the cash-flow betas [$\widehat{\beta}_{CF}$, defined in equation (9)] and discount-rate betas [$\widehat{\beta}_{CF}$, defined in equation (10)] for the 25 ME and BE/ME portfolios using a 120-month moving window. The value-minus-growth series, denoted by a solid line and triangles, is then constructed as the equal-weight average of the five extreme value (high BE/ME) portfolios' betas less that of the five extreme growth (low BE/ME) portfolios' betas. The small-minus-big series, denoted by a solid line, is constructed as the equal-weight average of the five extreme small (low ME) portfolios' betas less that of the five extreme large (high ME) portfolios' betas. The top panel shows the estimated cash-flow and the bottom panel estimated discount-rate betas. Dates on the horizontal axis denote the midpoint of the estimation window.

flows, and dependence on external equity finance lead to a high discount-rate beta. For example, if a distressed firm needed new equity financing simply to survive after the Great Depression, and if the availability and cost of such financing is related to the overall cost of capital, then such a firm's value is likely to have been very sensitive to discount-rate news. Similarly, new small firms with a negative current cash flow but valuable investment opportunities are likely to be very sensitive to discount-rate news. This higher sensitivity of young firms would explain why the discount-rate betas of small stocks increased sharply around the intial-public-offering (IPO) wave of 1960's, remained high as NASDAQ firms are included in our sample during the late 1970's, and sharply increased again with the flood of technology IPOs in the 1990's. Since these newly listed firms were sold to the public at extremely high multiples in the 1990's, this story is also consistent with the contemporaneous dramatic increase of growth stocks' discount-rate betas relative to value stocks' betas.

The overall trend in growth stocks' discount-rate betas may also be partially explained by changes in stock market listing requirements. During the early period, only firms with significant internal cash flow made it to the Big Board and thus our sample. This is because, in the past, the New York Stock Exchange had very strict profitability requirements for a firm to be listed on the exchange. The low-BE/ME stocks in the first half of the sample are thus likely be consistently profitable and independent of external financing. In contrast, our post-1963 sample also contains NASDAQ stocks and less-profitable new lists on the NYSE. These firms are listed precisely to improve their access to equity financing, and many of them will not even survive – let alone achieve their growth expectations – without a continuing availability of inexpensive equity financing.

Finally, it is possible that our discount-rate news is simply news about investor sentiment. If growth investing has become more popular among irrational investors during our sample period, growth stocks may have become more sensitive to shifts in the sentiment of these investors.

Our risk-sorted portfolios also have different betas over the two subsamples, as shown in Table 7. Sorting on market risk while controlling for other state variables results in a spread in both betas during the first subsample but induces a spread in only the discount-rate beta in the second subsample. Sorts on value-spread and term-spread sensitivities do not induce strong patterns in betas in either subsample.

Table 7: Subperiod betas for the risk-sorted portfolios

The table shows the estimates of cash-flow betas ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$) for the 20 risk-sorted portfolios for the two subperiods (1929:1-1963:6 and 1963:7-2001:12). Footnotes of Table 5 apply.

1929:1-1963:6

$\widehat{\beta}_{CF}$	Lo $\widehat{b}_{r_M}$		2		3		4		Hi $\widehat{b}_{r_M}$		Diff.	
Lo $\widehat{b}_{VS}$	.21	(.13)	.25	(.15)	.31	(.19)	.37	(.22)	.45	(.27)	.25	(.14)
Hi $\widehat{b}_{VS}$	.15	(.10)	.19	(.12)	.25	(.16)	.28	(.18)	.37	(.21)	.22	(.12)
Lo $\widehat{b}_{TY}$	.18	(.12)	.21	(.14)	.26	(.17)	.31	(.20)	.41	(.23)	.23	(.12)
Hi $\widehat{b}_{TY}$	.16	(.11)	.21	(.13)	.27	(.16)	.32	(.19)	.40	(.23)	.24	(.13)
$\widehat{\beta}_{DR}$	Lo $\widehat{b}_{r_M}$		2		3		4		Hi $\widehat{b}_{r_M}$		Diff.	
Lo $\widehat{b}_{VS}$	.73	(.14)	.87	(.16)	1.04	(.19)	1.20	(.23)	1.46	(.28)	.73	(.15)
Hi $\widehat{b}_{VS}$	.64	(.11)	.75	(.13)	.96	(.17)	1.09	(.19)	1.30	(.22)	.66	(.13)
Lo $\widehat{b}_{TY}$	.73	(.13)	.85	(.15)	1.00	(.18)	1.17	(.21)	1.38	(.25)	.64	(.13)
Hi $\widehat{b}_{TY}$	.65	(.12)	.76	(.14)	.88	(.16)	1.09	(.20)	1.34	(.24)	.69	(.14)

1963:7-2001:12

$\widehat{\beta}_{CF}$	Lo $\widehat{b}_{r_M}$		2		3		4		Hi $\widehat{b}_{r_M}$		Diff.	
Lo $\widehat{b}_{VS}$	.09	(.09)	.08	(.11)	.10	(.12)	.10	(.15)	.12	(.20)	.04	(.12)
Hi $\widehat{b}_{VS}$	.06	(.10)	.06	(.13)	.07	(.15)	.05	(.19)	.06	(.24)	-.01	(.14)
Lo $\widehat{b}_{TY}$	.06	(.11)	.04	(.12)	.08	(.14)	.08	(.17)	.06	(.23)	.00	(.14)
Hi $\widehat{b}_{TY}$	.09	(.09)	.07	(.12)	.09	(.13)	.08	(.16)	.10	(.20)	.00	(.12)
$\widehat{\beta}_{DR}$	Lo $\widehat{b}_{r_M}$		2		3		4		Hi $\widehat{b}_{r_M}$		Diff.	
Lo $\widehat{b}_{VS}$	.57	(.10)	.77	(.12)	.88	(.13)	1.12	(.16)	1.40	(.21)	.82	(.14)
Hi $\widehat{b}_{VS}$	.67	(.11)	.85	(.14)	1.06	(.16)	1.30	(.20)	1.58	(.25)	.91	(.17)
Lo $\widehat{b}_{TY}$	.73	(.12)	.86	(.13)	1.05	(.15)	1.23	(.18)	1.60	(.25)	.87	(.16)
Hi $\widehat{b}_{TY}$	.61	(.10)	.79	(.12)	.91	(.14)	1.11	(.17)	1.39	(.21)	.78	(.14)

4 Pricing cash-flow and discount-rate betas

So far, we have shown that in the period since 1963, there is a striking difference in the beta composition of value and growth stocks. The market betas of growth stocks are disproportionately composed of discount-rate betas rather than cash-flow betas. The opposite is true for value stocks.

Motivated by this finding, we next examine the validity of a long-horizon investor's first-order condition, assuming that the investor holds a 100% allocation to the market portfolio of stocks at all times. We ask whether the investor would be better off adding a margin-financed position in some of our test assets (such as value or small stocks), as a short-horizon investor's first-order condition would suggest.

Our main finding is that the long-horizon investor's first-order condition is not violated by our test assets and that the difference in beta composition can largely explain the high returns on value and low returns on growth stocks relative to the predictions of the static CAPM. The extreme small-growth portfolio remains an exception that our model cannot explain.

4.1 An intertemporal asset pricing model

Campbell (1993) derived an approximate discrete-time version of Merton's (1973) intertemporal CAPM. The model's central pricing statement is based on the first-order condition for an agent who holds a portfolio p of tradable assets that contains all of her wealth. Campbell then assumes that this condition holds for a representative agent who holds the market portfolio of all wealth to derive observable asset-pricing implications from the first-order condition.

In Campbell's (1993) model, the (representative) agent is infinitely lived and has the recursive preferences proposed by Epstein and Zin (1989, 1991):

$$U\left(C_t, \mathrm{E}_t\left(U_{t+1}\right)\right) = \left[(1-\delta)\, C_t^{\frac{1-\gamma}{\theta}} + \delta\left(\mathrm{E}_t\left(U_{t+1}^{1-\gamma}\right)\right)^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{11}$$

where C_t is consumption at time t, $\gamma > 0$ is the relative risk aversion coefficient, $\psi > 0$ is the elasticity of intertemporal substitution, $0 < \delta < 1$ is the time discount factor, and $\theta \equiv (1-\gamma)/(1-\psi^{-1})$. These preferences are a generalization of power utility, formalized with an objective function (U) that retains the desirable scale-independence of the power utility function. Deviating from the power-utility model, however, the Epstein-Zin preferences relax the restriction that the elasticity of intertemporal substitution must equal the reciprocal of the coefficient of relative risk aversion. In the Epstein-Zin model, the elasticity of intertemporal substitution, ψ, and the coefficient of relative risk aversion, γ, are both free parameters.

Campbell's (1993) approximate model also assumes that asset returns are conditionally lognormal. Returns must have constant variance unless the elasticity of intertemporal substitution equals one, in which case returns may be heteroskedastic. As a working assumption, we add tractability to the model by setting $\psi = 1$, since even this special case will be flexible enough to deliver realistic cross-sectional variation in the risk premia predicted by the model. In the $\psi = 1$ case, $\rho = \delta$ and the optimal consumption-wealth ratio is conveniently constant and equal to $1 - \rho$. Our choices of $\rho = .95^{1/12}$ and $\psi = 1$ thus imply that in the end of each month, the investor chooses to consume .43% of her wealth.[5]

Under these assumptions, Campbell (1993) shows that the optimality of portfolio strategy p requires that the risk premium on any asset i satisfies

$$\begin{aligned} \mathrm{E}_t[r_{i,t+1}] - r_{f,t+1} + \frac{\sigma_{i,t}^2}{2} &= \gamma \mathrm{Cov}_t(r_{i,t+1}, r_{p,t+1} - E_t r_{p,t+1}) \\ &\quad + (1-\gamma)\mathrm{Cov}_t(r_{i,t+1}, -N_{p,DR,t+1}), \end{aligned} \tag{12}$$

where p is the optimal portfolio that the agent chooses to hold and $N_{p,DR,t+1} \equiv (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{p,t+1+j}$ is discount-rate or expected-return news on this (possibly dynamic) portfolio strategy.

The left hand side of (12) is the expected excess log return on asset i over the riskless interest rate, plus one-half the variance of the excess return to adjust for Jensen's Inequality. This is the appropriate measure of the risk premium in a lognormal model. The right hand side of (12) is a weighted average of two covariances: the covariance of return i with the return on portfolio p, which gets a weight of γ, and the covariance of return i with negative of news about future expected returns on portfolio p, which gets a weight of $(1 - \gamma)$. These two covariances represent the myopic and intertemporal hedging components of asset demand, respectively. When $\gamma = 1$, it is well known that portfolio choice is myopic and the first-order condition collapses to the familiar one used to derive the pricing implications of the CAPM.

[5] Schroder and Skiadas (1999) examine this case in a continuous-time framework which eliminates the need for approximations if $\psi = 1$.

We can rewrite equation (12) to relate the risk premium to covariance with cash-flow news and discount-rate news. Since $r_{p,t+1} - E_t r_{p,t+1} = N_{p,CF,t+1} - N_{p,DR,t+1}$, we have

$$\mathrm{E}_t[r_{i,t+1}] - r_{f,t+1} + \frac{\sigma_{i,t}^2}{2} = \gamma \mathrm{Cov}_t(r_{i,t+1}, N_{p,CF,t+1}) + \mathrm{Cov}_t(r_{i,t+1}, -N_{p,DR,t+1}). \quad (13)$$

Multiplying and dividing by the conditional variance of portfolio p's return, $\sigma_{p,t}^2$, we obtain

$$\mathrm{E}_t[r_{i,t+1}] - r_{f,t+1} + \frac{\sigma_{i,t}^2}{2} = \gamma \sigma_{p,t}^2 \beta_{i,CF_p,t} + \sigma_{p,t}^2 \beta_{i,DR_p,t}. \quad (14)$$

This equation delivers our prediction that "bad beta" with cash-flow news should have a risk price γ times greater than the risk price of "good beta" with discount-rate news, which should equal the variance of the return on portfolio p.

4.2 Empirical estimates of premia for an all-stock investor

Would an all-stock investor be better off holding stocks at market weights or overweighing value and small stocks? We examine the validity of an unconditional version of the first-order condition (14) relative to the market portfolio of stocks. We modify (14) in three ways. First, we use simple expected returns, $\mathrm{E}_t[R_{i,t+1} - R_{rf,t+1}]$, on the left-hand side, instead of log returns, $\mathrm{E}_t[r_{i,t+1}] - r_{rf,t+1} + \sigma_{i,t}^2/2$. In the lognormal model, both expectations are the same, and by using simple returns we make our results easier to compare with previous empirical studies. Second, we condition down equation (13) to derive an unconditional version of (14) to avoid estimation of all required conditional moments. Finally, we change the subscript p to M and use all-stock investment in the market portfolio of stocks as the reference portfolio, reflecting the fact that we test the optimality of the market portfolio of stocks for the long-horizon investor. These modifications yield:

$$\mathrm{E}[R_i - R_f] = \gamma \sigma_M^2 \beta_{i,CF_M} + \sigma_M^2 \beta_{i,DR_M} \quad (15)$$

We assume that the log real risk-free rate is approximately constant. We make this assumption mainly because monthly inflation data are unreliable, especially over our long 1928:12-2001:12 sample period. This assumption is unlikely to have a major impact on our tests, since we focus on stock portfolios. The main practical implication of the constant-real-rate assumption is that cash-flow and discount-rate news computed from excess CRSP value-weight index returns are identically equivalent to news terms computed from real CRSP value-weight index returns.

We use 24 of the 25 size- and book-to-market sorted portfolios and the 20 risk-sorted portfolios as test assets on the left hand side of the unconditional first-order condition (15). We exclude the extreme small-growth portfolio from our tests because even unrestricted factor models such as the Fama and French (1993) model are unable to explain the low returns on this portfolio. In fact, recent evidence on small growth stocks by Lamont and Thaler (2001), Mitchell, Pulvino, and Stafford (2002), D'Avolio (2002) and others suggests that the pricing of some small growth stocks is materially affected by short-sale constraints and other limits to arbitrage. Our traditional approach that builds on the frictionless rational expectations model is thus unlikely to ever yield a satisfactory explanation for the very low returns on the smallest growth stocks. Although we exclude the extreme small-growth portfolio from the premia estimation regressions, we later briefly discuss the pricing error of this portfolio given our estimated premia.

Tables 8 and 9 show the average returns to be explained by the cash-flow and discount-rate betas. Table 8 replicates the known results that value stocks and small stocks have outperformed growth stocks and large stocks in both subsamples. Only in the extreme growth quintile have small stocks have underperformed large stocks; in this case the book-to-market effect within the growth quintile overwhelms the size effect. The risk-sorted portfolios in Table 9 show distinct subperiod behavior. Over both subsamples, there is modest but consistent variation in average returns across different rows that are sorted on past value-spread loadings. Interestingly, sorts on past market-return loadings induce a strong spread in average returns over the first subperiod, but no spread at all over the second subperiod.

Table 10 evaluates the performance of the two-beta intertemporal asset pricing model in relation to an unrestricted two-beta model and the traditional CAPM with a single market beta. Each model is estimated in two different forms: one with a restricted zero-beta rate equal to the Treasury bill rate, and one with an unrestricted zero-beta rate (see Black 1972). Thus the table includes six columns in all, two for each of the three models. The first panel of Table 10 uses 24 of Davis, Fama, and French's (2000) 25 portfolios sorted on size and book-to-market ratio. The second panel adds our 20 risk-sorted portfolios to the set of test assets.

The first nine rows of Table 10 are divided into three sets of three rows. The first set of three rows corresponds to the zero-beta rate, the second set to the premium

Table 8: Average returns on the 25 ME and BE/ME portfolios

The table shows the sample average simple returns for Davis, Fama, and French's (2000) 25 size- and book-to-market-sorted portfolios. Returns are annualized and in percentage points (monthly fractions multiplied by 1200). Standard errors are in square brackets. "Growth" denotes the lowest BE/ME, "Value" the highest BE/ME, "Small" the lowest ME, and "Large" the highest ME stocks. "Diff." is the difference between the extreme cells of the particular row or column. The first panel shows the estimates for the full 1929:1-2001:12 period, the second panel for the first subperiod (1929:1-1963:6), and the third panel for the second subperiod (1963:7-2001:12).

1929:1-2001:12

$\widehat{\mathrm{E}}(R)$	Growth	2	3	4	Value	Diff.
Small	9.17 [5.29]	13.37 [4.45]	15.91 [3.89]	18.24 [3.70]	19.72 [4.05]	10.55 [3.28]
2	10.07 [3.37]	14.59 [3.25]	16.06 [3.13]	16.40 [3.14]	17.69 [3.59]	7.62 [2.04]
3	11.35 [3.21]	13.69 [2.75]	14.62 [2.82]	15.55 [2.82]	16.64 [3.53]	5.28 [1.99]
4	11.38 [2.59]	11.92 [2.61]	13.89 [2.61]	14.90 [2.93]	16.54 [3.77]	5.16 [2.49]
Large	10.54 [2.29]	10.41 [2.19]	11.78 [2.38]	12.76 [2.85]	15.84 [3.50]	5.30 [2.44]
Diff.	1.37 [4.17]	-2.96 [3.34]	-4.14 [2.68]	-5.48 [2.21]	-3.88 [2.56]	

1929:1-1963:6

$\widehat{\mathrm{E}}(R)$	Growth	2	3	4	Value	Diff.
Small	9.14 [9.85]	11.20 [8.29]	15.74 [7.27]	18.21 [6.89]	20.29 [7.68]	11.14 [6.37]
2	9.30 [5.28]	15.53 [5.68]	15.47 [5.63]	15.34 [5.78]	17.31 [6.69]	8.01 [3.39]
3	11.80 [5.12]	12.86 [4.69]	14.83 [5.07]	14.80 [5.19]	15.35 [6.73]	3.54 [3.18]
4	10.12 [3.89]	12.23 [4.47]	13.48 [4.64]	13.65 [5.50]	16.09 [7.25]	5.96 [4.52]
Large	9.50 [3.74]	9.05 [3.59]	11.38 [4.23]	12.08 [5.41]	18.36 [6.82]	8.86 [4.52]
Diff.	0.35 [7.97]	-2.15 [6.22]	-4.37 [4.79]	-6.13 [3.66]	-1.93 [4.57]	

1963:7-2001:12

$\widehat{\mathrm{E}}(R)$	Growth	2	3	4	Value	Diff.
Small	9.19 [4.69]	15.32 [4.02]	16.07 [3.49]	18.26 [3.29]	19.21 [3.41]	10.02 [2.38]
2	10.75 [4.21]	13.76 [3.44]	16.58 [3.04]	17.36 [2.92]	18.03 [3.22]	7.28 [2.38]
3	10.95 [3.89]	14.43 [3.10]	14.44 [2.78]	16.22 [2.64]	17.80 [2.99]	6.84 [2.52]
4	12.50 [3.48]	11.65 [2.91]	14.25 [2.72]	16.02 [2.61]	16.94 [2.95]	4.43 [2.54]
Large	11.46 [2.76]	11.63 [2.58]	12.14 [2.44]	13.37 [2.39]	13.59 [2.62]	4.43 [2.39]
Diff.	2.27 [3.46]	-3.69 [3.14]	-3.93 [2.72]	-4.90 [2.63]	-5.63 [2.63]	

Table 9: Average returns on the risk-sorted portfolios

The table shows the sample average simple returns for the 20 risk-sorted portfolios. Returns are annualized and in percentage points (monthly fractions multiplied by 1200). Standard errors are in square brackets. The first panel shows the estimates for the full 1929:1-2001:12 period, the second panel for the first subperiod (1929:1-1963:6), and the third panel for the second subperiod (1963:7-2001:12). The construction of the risk-sorted portfolios is explained in the text and in the notes for Table 5.

1929:1-2001:12

$\widehat{\mathrm{E}}(R)$	Lo $\widehat{b}_{r_M}$	2	3	4	Hi $\widehat{b}_{r_M}$	Diff.
Lo $\widehat{b}_{VS}$	11.27 [2.02]	12.98 [2.39]	12.59 [2.75]	12.92 [3.20]	13.92 [3.93]	2.64 [2.58]
Hi $\widehat{b}_{VS}$	10.11 [1.77]	10.64 [2.07]	11.50 [2.50]	11.59 [2.88]	12.70 [3.56]	2.59 [2.47]
Lo $\widehat{b}_{TY}$	10.03 [1.96]	11.85 [2.20]	12.04 [2.63]	12.88 [3.04]	12.54 [3.74]	2.51 [2.49]
Hi $\widehat{b}_{TY}$	10.23 [1.83]	11.81 [2.14]	11.88 [2.42]	12.69 [2.88]	13.04 [3.55]	2.81 [2.45]

1929:1-1963:6

$\widehat{\mathrm{E}}(R)$	Lo $\widehat{b}_{r_M}$	2	3	4	Hi $\widehat{b}_{r_M}$	Diff.
Lo $\widehat{b}_{VS}$	9.78 [3.51]	12.58 [4.41]	11.70 [5.09]	11.97 [5.92]	14.58 [7.26]	4.79 [4.56]
Hi $\widehat{b}_{VS}$	8.69 [2.77]	9.81 [3.41]	12.58 [4.27]	12.50 [4.91]	13.89 [6.00]	5.20 [3.90]
Lo $\widehat{b}_{TY}$	7.92 [3.20]	11.80 [3.82]	11.47 [4.67]	13.53 [5.40]	12.14 [6.43]	4.22 [3.96]
Hi $\widehat{b}_{TY}$	8.03 [2.98]	10.81 [3.68]	11.75 [4.28]	13.32 [5.13]	14.10 [6.41]	6.07 [4.23]

1963:7-2001:12

$\widehat{\mathrm{E}}(R)$	Lo $\widehat{b}_{r_M}$	2	3	4	Hi $\widehat{b}_{r_M}$	Diff.
Lo $\widehat{b}_{VS}$	12.60 [2.18]	13.34 [2.28]	13.39 [2.56]	13.77 [3.07]	13.32 [3.79]	.72 [2.89]
Hi $\widehat{b}_{VS}$	11.37 [2.24]	11.38 [2.49]	10.53 [2.86]	10.77 [3.37]	11.63 [4.19]	.25 [3.20]
Lo $\widehat{b}_{TY}$	11.92 [2.36]	11.90 [2.43]	12.56 [2.80]	12.31 [3.28]	12.91 [4.22]	.98 [3.18]
Hi $\widehat{b}_{TY}$	12.20 [2.23]	12.70 [2.34]	11.99 [2.56]	12.13 [3.02]	12.09 [3.72]	-.11 [2.85]

Table 10: Asset pricing tests for the full sample (1929:1-2001:12)

The table shows estimated premia for an unrestricted factor model, the two-beta ICAPM, and the CAPM. For each model, the second column constrains the zero-beta rate (R_{zb}) to equal the risk-free rate (R_{rf}). Estimates are from a cross-sectional regression of average simple excess test-asset returns (monthly in fractions) on an intercept and estimated cash-flow ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$). The test rejects if the pricing error is higher than the listed 5% critical value.

24 ME and BE/ME portfolios

Parameter	Factor model		Two-beta ICAPM		CAPM	
R_{zb} less R_{rf} (g_0)	.0026	0	-.0013	0	-.0006	0
Std. err.	(.0050)	N/A	(.0049)	N/A	(.0040)	N/A
% per annum	3.16%	0%	-1.52%	0%	-.67%	0%
$\widehat{\beta}_{CF}$ premium (g_1)	.0324	.0322	.0258	.0212	.0068	.0064
Std. err.	(.0342)	(.0294)	(.0314)	(.0443)	(.0047)	(.0021)
% per annum	38.85%	38.66%	30.99%	25.39%	8.21%	7.72%
$\widehat{\beta}_{DR}$ premium (g_2)	-.0022	.0003	.0030	.0030	.0068	.0064
Std. err.	(.0079)	(.0067)	(.0003)	(.0003)	(.0047)	(.0021)
% per annum	-2.58%	.34%	3.62%	3.62%	8.21%	7.72%
$\widehat{R}^2$	78.52%	76.01%	70.64%	68.72%	38.04%	37.92%
Pricing error	5.15	5.75	7.04	7.50	14.86	14.89
5% critic. val.	17.08	23.86	21.86	227.35	20.88	34.56

24 ME and BE/ME portfolios and 20 risk-sorted portfolios

Parameter	Factor model		Two-beta ICAPM		CAPM	
R_{zb} less R_{rf} (g_0)	.0036	0	.0003	0	.0022	0
Std. err.	(.0020)	N/A	(.0025)	N/A	(.0019)	N/A
% per annum	4.33%	0%	.33%	0%	2.61%	0%
$\widehat{\beta}_{CF}$ premium (g_1)	.0335	.0328	.0182	.0193	.0043	.0059
Std. err.	(.0303)	(.0295)	(.0217)	(.0407)	(.0029)	(.0020)
% per annum	40.16%	39.37%	21.87%	23.18%	5.15%	7.12%
$\widehat{\beta}_{DR}$ premium (g_2)	-.0036	-.0001	.0030	.0030	.0043	.0059
Std. err.	(.0072)	(.0066)	(.0003)	(.0003)	(.0029)	(.0020)
% per annum	-4.27%	-.13%	3.62%	3.62%	5.15%	7.12%
$\widehat{R}^2$	78.67%	66.14%	56.67%	56.52%	34.04%	29.25%
Pricing error	9.39	14.90	19.07	19.13	29.02	31.13
5% critic. val.	35.16	31.73	39.92	218.46	41.79	39.78

on cash-flow beta, and the third set to the premium on discount-rate beta. With each set, the first row reports the premium point estimate in fractions per month, the second row the standard error of the estimate, and third row an annualized version of the estimate (produced by multiplying the first row by 1200 and presented to make the interpretation of the estimate more convenient). The premia are estimated with a cross-sectional regression

$$\overline{R}_i^e = g_0 + g_1\widehat{\beta}_{i,CF} + g_2\widehat{\beta}_{i,DR} + e_i, \tag{16}$$

where bar denotes time-series mean and $\overline{R}_i^e \equiv \overline{R}_i - \overline{R}_{rf}$ denotes the sample average simple excess return on asset i. The implied risk-aversion coefficient can be recovered as g_1/g_2.

The first panel of Table 10 shows that the unrestricted factor model attaches a relatively high premium, 39% per annum, to the cash-flow beta. The premium on discount-rate beta is much lower, -2.6% per annum when the intercept is a free parameter and .34% when the intercept is constrained to zero. These premia obtained from an unrestricted factor model are remarkably similar to the premia estimated under the ICAPM restriction on the discount-rate-beta premium. The estimated cash-flow-beta premium for the constrained model in the first panel of Table 10 is 31% per annum with a free intercept and 25% with a constrained intercept. Discount-rate beta carries a premium of 3.6%, which is comfortably close to the unrestricted estimates, considering the sampling uncertainty in these estimates. The implied risk-aversion coefficient of the representative investor is 8.6 with a free intercept and 7.0 with a restricted intercept. This is well within the range considered reasonable in the recent literature on the equity premium puzzle.

Contrary to the ICAPM premia, the premia estimated from the static CAPM are far from those of the unrestricted factor model. The static CAPM is forced to pick the same premium for cash-flow and discount rate betas, and the estimated value around 8% per annum does not really fit either cash-flow or discount-rate betas.

Below the premia estimates, we report the $\widehat{R}^2$ statistic for a cross-sectional regression of average returns on our test assets onto the fitted values from the model, the composite pricing error, and the 5% critical value for the composite pricing error. The composite pricing error is computed as $\widehat{e}'\widehat{\Omega}^{-1}\widehat{e}$, where $\widehat{e}$ is the vector of estimated residuals from regression (16) and $\widehat{\Omega}$ is the sample covariance matrix of test asset returns. The weighting matrix, $\widehat{\Omega}^{-1}$, in the composite pricing error formula places less weight on noisy observations yet it is independent of the specific pricing model.

The regression $\widehat{R}^2$ is computed as

$$\widehat{R}^2 = 1 - \frac{\widehat{e}'\widehat{e}}{\left(\overline{R}_i^e - \sum_i \overline{R}_i^e\right)' \left(\overline{R}_i^e - \sum_i \overline{R}_i^e\right)} \, , \tag{17}$$

which allows for negative $\widehat{R}^2$ for poorly fitting models estimated under the constraint that the zero-beta rate equals the risk-free rate.

Standard errors and the 5% critical values are produced with bootstrap from 2500 simulated realizations. Our bootstrap experiment samples test-asset returns and VAR errors, and uses the OLS VAR estimates in Table 2 to generate the state-variable data. We partition the VAR errors and test-asset returns into two groups, one for 1929:1-1963:6 and another for 1963:7-2001:12, which enables us to use the same simulated realizations in subperiod analyses. The VAR and the news terms, cash-flow and discount-rate betas, and the premia are then all estimated for each simulated realization. Our standard errors thus incorporate the considerable additional sampling uncertainty due to the fact that the news terms as well as betas are generated regressors. The 5% critical values are produced with a similar bootstrap method, except that the test-asset returns are adjusted to be consistent with the pricing model before the random samples are generated.

Over the full 1929:1–2001:12 sample and using the 24 size and book-to-market portfolios as test assets, the traditional CAPM can explain about 38% of the cross-sectional variation in average returns on our test assets. Although the traditional CAPM does a respectable job in explaining the average test-asset returns and is not rejected by our composite-pricing-error test, the intertemporal CAPM does considerably better, explaining 69% of the variation when we impose the Treasury bill rate as the zero-beta rate, and 71% when we allow a free zero-beta rate. In the latter case the model sets the zero-beta rate slightly lower than the average Treasury bill rate. An unrestricted two-beta model does even better. This model allows free risk prices for cash-flow beta and discount-rate beta rather than imposing that discount-rate beta have a risk price equal to the variance of the market return. It assigns a slightly negative risk price for discount-rate beta, treating it as "good" in absolute terms rather than only good relative to cash-flow beta. The unrestricted model explains 76–79% of the cross-sectional variation in average returns on the test assets.

Daniel and Titman (1997) emphasize the importance of testing asset pricing models also on risk-sorted portfolios, not only on portfolios sorted on characteristics known to be strongly related to average returns. Characteristics-sorted portfolios are likely to show some spread in betas identified as risk by almost any model, at least in sample. Then the cross-sectional regression (16) might attach a high premium per unit of beta to fit the large variation in average returns. Thus, at least when premia are not constrained by theory, an asset pricing model may spuriously look successful in explaining the average returns to characteristics-sorted portfolios.

To alleviate this concern, the second panel of Table 10 includes 20 risk-sorted portfolios in the set of test assets. If the success in the first panel was a spurious result due to an unrestricted premium on cash-flow beta, these additional 20 test assets should expose the model. Our two-beta ICAPM survives this challenge. For the model that constrains the zero-beta rate to equal the risk-free rate, for example, the addition of risk-sorted portfolios reduces the premium on cash-flow beta only slightly (from 25% to 23% per annum). In general, the conclusions drawn from the first panel are basically unchanged by the addition of the risk-sorted portfolios in the second panel, which is good news for our two-beta ICAPM specification.

In unreported tests, we also compare the two-beta model to the influential three-factor APT specification by Fama and French (1993). The Fama-French model includes three risk factors, one each for the market, small stocks, and value stocks. We estimate the betas for each test asset from simple returns using Ibbotson's sum-beta methodology with one lag and then regress the average excess test-asset returns on the estimated betas. Over the full sample period and using the 24 size and book-to-market portfolios as test assets, the Fama-French three-factor model obtains an estimated R^2 of 86% with an unconstrained zero-beta rate and 69% with a zero-beta rate constrained to the risk-free rate. The Fama-French model's R^2 is 15 percentage points higher than our two-beta model's in the first case, and exactly equal to the two-beta model's in the second case. When we add the risk-sorted portfolios to the set of test assets, the Fama-French model explains 84% and 62% of the variation in average returns, depending on whether the intercept is constrained. While the former Fama-French specification again outperforms the two-beta model by 27 percentage points, the latter specification outperforms the corresponding two-beta specification by only 4 percentage points. Given that the Fama-French model has three freely estimated betas and thus two additional degrees of freedom (since the premium on discount-rate beta is restricted to equal the variance of the market's return in our model), we consider the relative performance of the two-beta ICAPM to be a striking success.

Since the beta patterns vary across subsamples, we also estimate the cross-sectional

Table 11: Asset pricing tests for the first subsample (1929:1-1963:6)
The table shows premia estimated from the 1929:1-1963:6 sample for an unrestricted factor model, the two-beta ICAPM, and the CAPM. The second column per model constrains the zero-beta rate (R_{zb}) to equal the risk-free rate (R_{rf}). Estimates are from a cross-sectional regression of average simple excess test-asset returns (monthly in fractions) on an intercept and estimated cash-flow ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$). The test rejects if the pricing error is higher than the listed 5% critical value.

24 ME and BE/ME portfolios

Parameter	Factor model		Two-beta ICAPM		CAPM	
R_{zb} less R_{rf} (g_0)	.0067	0	.0005	0	.0000	0
Std. err.	(.0052)	N/A	(.0044)	N/A	(.0046)	N/A
% per annum	8.07%	0%	.63%	0%	.01%	0%
$\widehat{\beta}_{CF}$ premium (g_1)	.0353	.0213	.0150	.0164	.0071	.0071
Std. err.	(.0271)	(.0260)	(.0266)	(.0482)	(.0058)	(.0035)
% per annum	42.35%	25.56%	17.97%	19.68%	8.48%	8.48%
$\widehat{\beta}_{DR}$ premium (g_2)	-.0078	.0025	.0041	.0041	.0071	.0071
Std. err.	(.0105)	(.0073)	(.0005)	(.0005)	(.0058)	(.0035)
% per annum	-9.39%	3.05%	4.95%	4.95%	8.48%	8.48%
$\widehat{R}^2$	64.48%	56.22%	55.71%	55.45%	49.87%	49.87%
Pricing error	8.53	10.50	10.63	10.69	12.03	12.03
5% critic. val.	20.28	26.60	24.53	118.76	22.41	33.78

24 ME and BE/ME portfolios and 20 risk-sorted portfolios

Parameter	Factor model		Two-beta ICAPM		CAPM	
R_{zb} less R_{rf} (g_0)	.0050	0	.0014	0	.0015	0
Std. err.	(.0028)	N/A	(.0029)	N/A	(.0027)	N/A
% per annum	6.04%	0%	1.69%	0%	1.83%	0%
$\widehat{\beta}_{CF}$ premium (g_1)	.0313	.0175	.0115	.0156	.0057	.0068
Std. err.	(.0253)	(.0235)	(.0223)	(.0452)	(.0044)	(.0034)
% per annum	37.54%	21.05%	13.83%	18.75%	6.89%	8.16%
$\widehat{\beta}_{DR}$ premium (g_2)	-.0052	.0035	.0041	.0041	.0057	.0068
Std. err.	(.0088)	(.0070)	(.0006)	(.0006)	(.0044)	(.0034)
% per annum	-6.25%	4.24%	4.95%	4.95%	6.89%	8.16%
$\widehat{R}^2$	68.40%	56.66%	59.37%	56.55%	55.11%	53.23%
Pricing error	13.90	19.07	17.88	19.12	19.75	20.58
5% critic. val.	38.46	43.50	47.67	128.55	41.74	49.61

pricing regressions in both subsamples. Table 11 and Figure 3 show results for the first subsample (1929:1-1963:6), and Table 12 and Figure 4 show results for the second subsample (1963:7-2001:12). Both figures plot the predicted average excess return on the horizontal axis and the actual sample average excess return on the vertical axis. For a model with a 100% estimated R^2, all the points would fall on the 45-degree line displayed in each graph. The triangles in the figures denote the 24 Fama-French portfolios and asterisks the 20 risk-sorted portfolios.

It is evident from Table 12 and Figure 4 that the superior performance of the intertemporal CAPM relative to the static CAPM is concentrated in the second subsample. In this period the static CAPM fails disastrously to explain the returns on the test assets. When the zero-beta rate is left a free parameter, the cross-sectional regression picks a negative premium for the CAPM beta and implies a near-zero estimated R^2. When the zero-beta rate is constrained to the risk-free rate, the CAPM $\widehat{R}^2$ falls to -40%, i.e., the model has larger pricing error than the null hypothesis that all portfolios have equal expected returns. The static CAPM is also rejected at the 5% level for both sets of test assets.

In the first subsample, the static CAPM performs about as well as either of the two-beta models. The $\widehat{R}^2$s of the CAPM and ICAPM in Table 11 are close to each other at approximately 50% and the pricing scatter plots in Figure 3 are nearly identical. The good performance of the CAPM in this period can be traced back to the fact that the bad cash-flow beta is roughly a constant fraction of the CAPM beta across test assets. Thus, our tests cannot discriminate between the static and intertemporal CAPM models in the first subperiod.

Although the two-beta model is generally quite successful in explaining the cross-section of average returns, the model cannot price the extreme small-growth portfolio omitted from our main tests. In the first subsample, the extreme small-growth portfolio has an annualized average return that is 8.9 percentage points lower than the model's prediction. In the second subsample, this return on this portfolio is 4.6 percentage points lower than the model's prediction. These pricing-error calculations use premia estimated from the larger test-asset set for the model specification with the zero-beta rate constrained to the risk-free rate. In both subsamples, the pricing errors are economically large and not meaningfully smaller than the Sharpe-Lintner CAPM's pricing errors (7.5 percentage points in the first and 7.9 percentage points in the second subsample).

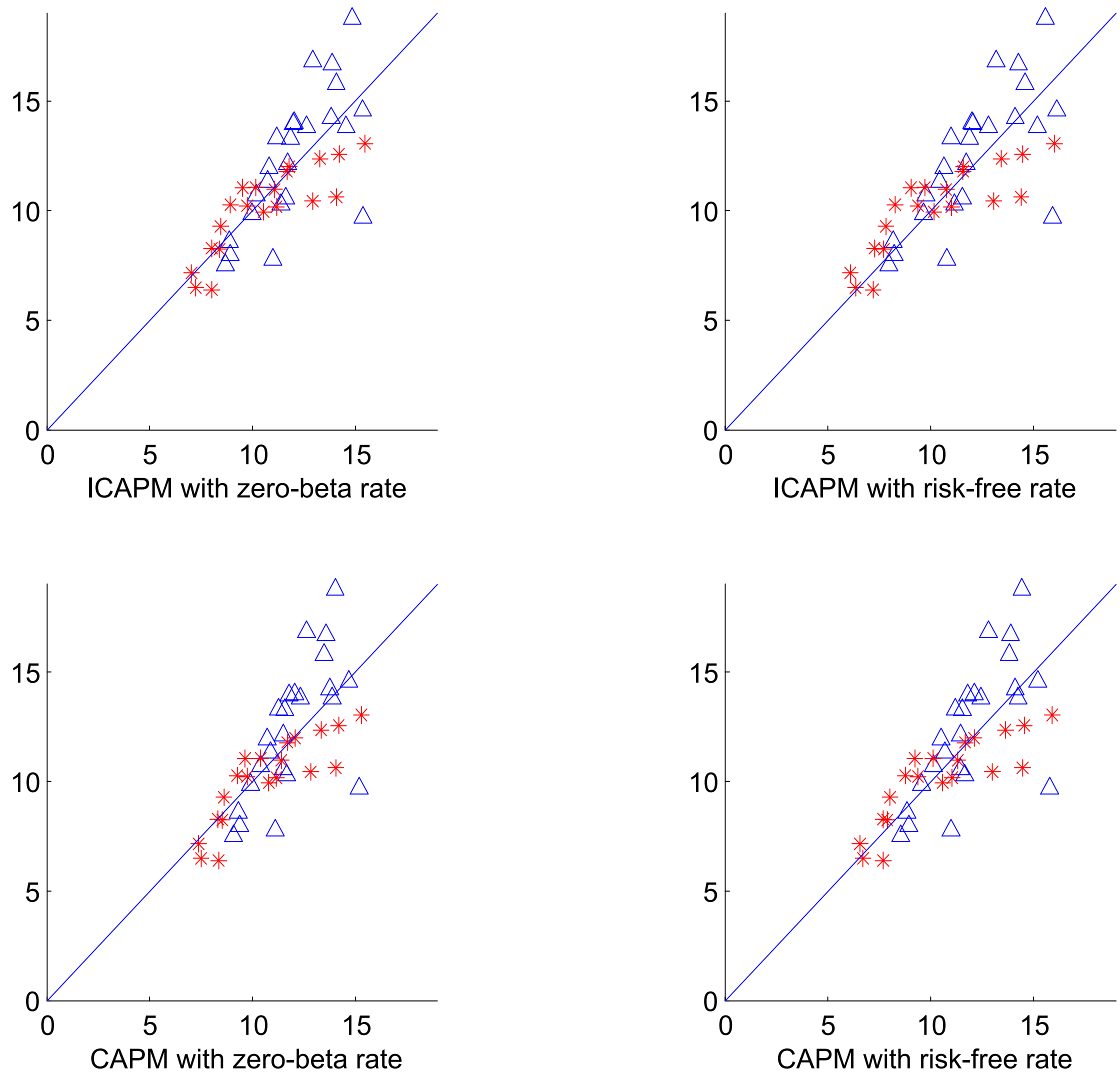

Figure 3: Performance of the CAPM and ICAPM, 1929:1-1963:6.

The four diagrams correspond to (clockwise from the top left) the ICAPM with a free zero-beta rate, the ICAPM with the zero-beta rate constrained to the risk-free rate, the CAPM with a constrained zero-beta rate, and the CAPM with an unconstrained zero-beta rate. The horizontal axes correspond to the predicted average excess returns and the vertical axes to the sample average realized excess returns. The predicted values are from regressions presented in the bottom panel of Table 11. Triangles denote the 24 ME and BE/ME portfolios and asterisks the 20 risk-sorted portfolios.

Table 12: Asset pricing tests for the second subsample (1963:7-2001:12)

The table shows premia estimated from the 1963:7-2001:12 sample for an unrestricted factor model, the two-beta ICAPM, and the CAPM. The second column per model constrains the zero-beta rate (R_{zb}) to equal the risk-free rate (R_{rf}). Estimates are from a cross-sectional regression of average simple excess test-asset returns (monthly in fractions) on an intercept and estimated cash-flow ($\widehat{\beta}_{CF}$) and discount-rate betas ($\widehat{\beta}_{DR}$). The test rejects if the pricing error is higher than the listed 5% critical value.

24 ME and BE/ME portfolios

Parameter	Factor model		Two-beta ICAPM		CAPM	
R_{zb} less R_{rf} (g_0)	-.0039	0	-.0002	0	.0079	0
Std. err.	(.0083)	N/A	(.0056)	N/A	(.0043)	N/A
% per annum	-4.69%	0%	-.25%	0%	9.49%	0%
$\widehat{\beta}_{CF}$ premium (g_1)	.0689	.0533	.0571	.0550	-.0007	.0061
Std. err.	(.0518)	(.0559)	(.0417)	(.0528)	(.0049)	(.0024)
% per annum	82.63%	63.93%	68.47%	67.00%	-.86%	7.35%
$\widehat{\beta}_{DR}$ premium (g_2)	.0046	.0022	.0020	.0020	-.0007	.0061
Std. err.	(.0139)	(.0123)	(.0002)	(.0002)	(.0049)	(.0024)
% per annum	5.49%	2.65%	2.43%	2.43%	-.86%	7.35%
$\widehat{R}^2$	66.52%	62.32%	66.24%	62.14%	.05%	-40.98%
Pricing error	8.03	9.04	9.06	9.08	22.88	33.83
5% critic. val.	21.33	56.60	30.14	275.42	22.85	43.87

24 ME and BE/ME portfolios and 20 risk-sorted portfolios

Parameter	Factor model		Two-beta ICAPM		CAPM	
R_{zb} less R_{rf} (g_0)	.0005	0	-.0006	0	.0062	0
Std. err.	(.0035)	N/A	(.0030)	N/A	(.0034)	N/A
% per annum	.56%	0%	-.66%	0%	7.44%	0%
$\widehat{\beta}_{CF}$ premium (g_1)	.0522	.0545	.0547	.0488	-.0000	.0053
Std. err.	(.0331)	(.0430)	(.0255)	(.0423)	(.0034)	(.0024)
% per annum	62.68%	65.36%	65.66%	58.59%	-.03%	6.33%
$\widehat{\beta}_{DR}$ premium (g_2)	.0012	.0015	.0020	.0020	-.0000	.0053
Std. err.	(.0090)	(.0094)	(.0002)	(.0002)	(.0034)	(.0024)
% per annum	1.48%	1.79%	2.43%	2.43%	-.03%	6.33%
$\widehat{R}^2$	52.68%	52.52%	51.63%	50.84%	.02%	-49.89%
Pricing error	20.82	20.89	21.28	21.63	43.00	65.95
5% critic. val.	41.23	66.99	55.44	360.11	42.89	60.85

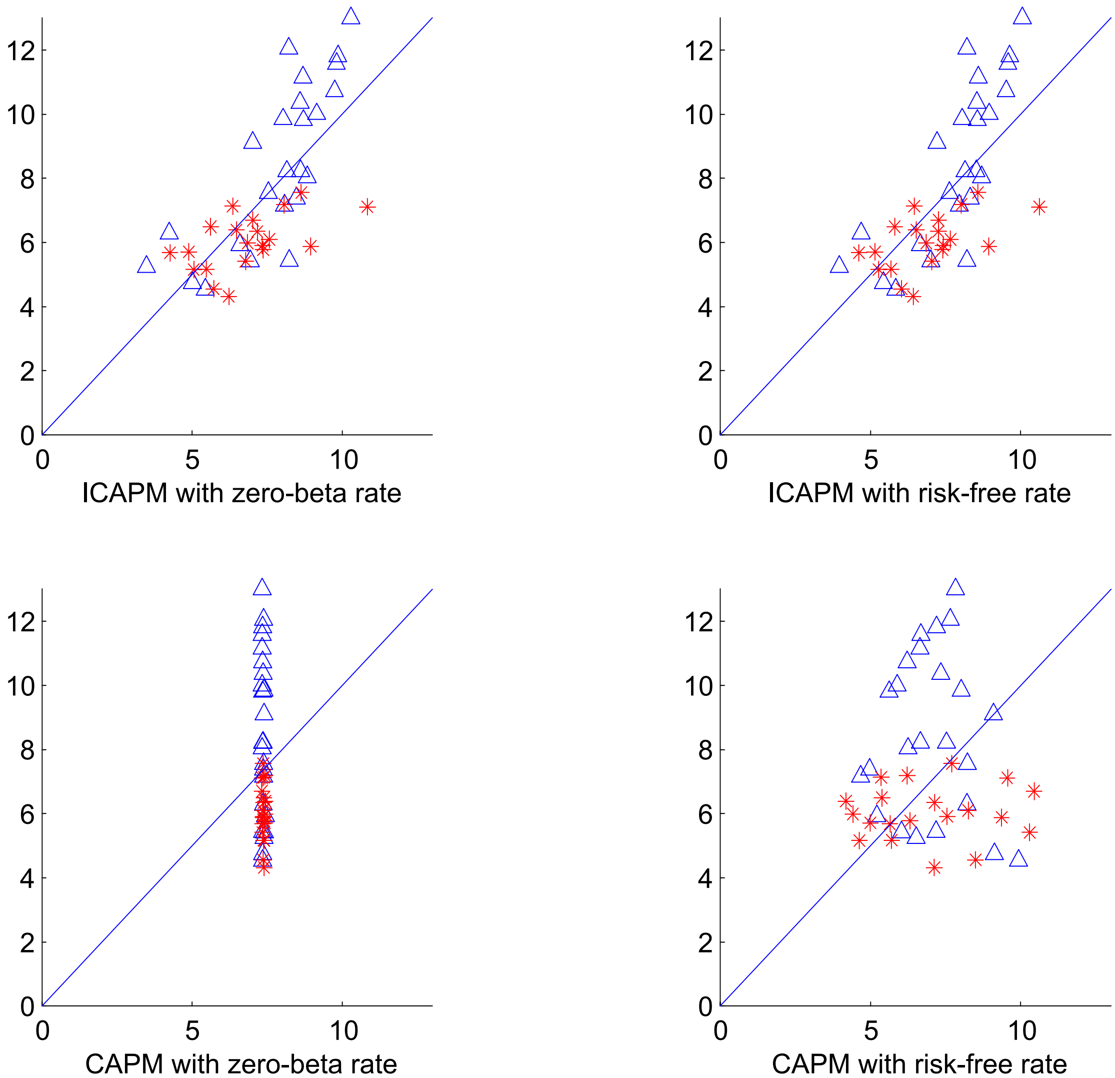

Figure 4: Performance of the CAPM and ICAPM, 1963:7-2001:12.

The four diagrams correspond to (clockwise from the top left) the ICAPM with a free zero-beta rate, the ICAPM with the zero-beta rate constrained to the risk-free rate, the CAPM with a constrained zero-beta rate, and te CAPM with an unconstrained zero-beta rate. The horizontal axes correspond to the predicted average excess returns and the vertical axes to the sample average realized excess returns. The predicted values are from regressions presented in the bottom panel of Table 12. Triangles denote the 24 ME and BE/ME portfolios and asterisks the 20 risk-sorted portfolios.

4.3 Risks to a strategic asset allocator

The above analysis assumes that the rational long-term investor always holds 100% of her assets in the market portfolio of stocks and invests nothing in the risk-free asset. But if expected returns on stocks vary over time (as suggested by the first VAR equation that predicts excess returns in Table 2) while the risk-free rate and the volatility of the stock market are approximately constant, the long-term investor has an obvious incentive to strategically time the market. In this subsection, we examine whether a long-term investor who strategically allocates wealth into stocks and bonds would be better off overweighting small and value stock than holding the stock portion of her portfolio at market weights.

To examine the impact of market timing on the long-horizon investor's first-order condition, we focus on an investor who times her stock-market exposure based on low-frequency swings in the overall valuation level. Our modeling strategy is the following: First, we summarize the discount-rate information in the VAR model of Table 2 into a single measure, the price of future discount rates. Second, we simplify the investor's asset-allocation problem by assuming that (1) the price of future discount rates follows a univariate first-order autoregression, (2) the log real risk-free rate is constant, (3) the expected one-period excess stock return is a linear function of the price of future discount rates, and (4) the volatility of stock returns is constant. These assumptions map our model into the framework of Campbell and Viceira (1999). We estimate the parameters of this simplified return-generating process with OLS regressions. Third, we compute returns and news terms on portfolio strategies that time the weight in market portfolio of stocks as a linear function of the market's overall valuation level. Fourth and finally, we test whether the average returns on our test assets violate the strategic asset allocator's first-order condition.

We begin by summarizing the discount-rate information in our four-variable VAR into a single state variable. Define the price of future discount rates for the market portfolio of stocks, $p_{M,DR}$, as

$$p_{M,DR,t} = \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j [r^e_{M,t+1+j} - \mathrm{E}(r^e_M)] = \rho^{-1} e1'\lambda[z_t - \mathrm{E}(z_t)]. \tag{18}$$

We use the fitted value of λ from Table 3.

Given the fitted values of $p_{M,DR}$, we estimate the following restricted VAR model:

$$\begin{bmatrix} r^e_{M,t+1} \\ \widehat{p}_{M,DR,t+1} \end{bmatrix} = \begin{bmatrix} c_{0,0} \\ c_{1,0} \end{bmatrix} + \begin{bmatrix} c_{0,1} \\ c_{1,1} \end{bmatrix} \widehat{p}_{M,DR,t} + \begin{bmatrix} w_{1,t+1} \\ w_{2,t+1} \end{bmatrix}. \tag{19}$$

We assume that the error vector is drawn from i.i.d. $N(0, \Sigma_w)$. Given the normality assumption and the fact that both equations in (19) share the same explanatory variable, OLS estimates of the restricted VAR's parameters are equal to conditional maximum likelihood estimates.

Denote the current equity premium by $x_t \equiv \mathrm{E}_t r^e_{M,t+1}$. Furthermore, suppose that the conditional equity premium follows a first-order autoregressive process and that realized returns are homoskedastic:

$$\begin{aligned} r^e_{M,t+1} &= x_t + u_{t+1} \\ x_{t+1} &= \mu + \phi(x_t - \mu) + \eta_{t+1}, \end{aligned} \tag{20}$$

where η is a normally distributed conditionally homoskedastic white noise error term with conditional variance σ^2_η. The unexpected excess return on the market portfolio of stocks, u, is homoskedastic with variance σ^2_u and with covariance $\sigma_{u\eta}$ with the shock to the conditional equity premium.

The parameters of (20) can be recovered from (19) using formulas $\mu = c_{0,0} + c_{0,1}c_{1,0}/(1 - c_{1,1})$, $\phi = c_{1,1}$, $\sigma^2_\eta = c^2_{0,1}\Sigma_{w22}$, $\sigma^2_u = \Sigma_{w11}$, $\sigma_{u\eta} = c_{0,1}\Sigma_{w12}$, and $x_t = c_{0,0} + c_{0,1}\widehat{p}_{M,DR,t}$. These derived parameter estimates are shown in (21). The reported standard errors (in parentheses) are generated from 2500 simulated realizations with a bootstrap procedure that takes into account the estimation uncertainty in the construction of $\widehat{p}_{M,DR}$.

$$\begin{aligned} x_{t+1} &= \underset{(.000979)}{.00405} + \underset{(.00641)}{.987}\,(x_t - \underset{(.000979)}{.00405}) + \eta_{t+1} \\ \sigma^2_\eta &= \underset{(8.06\times10^{-7})}{8.07 \times 10^{-7}}, \sigma^2_u = \underset{(.000289)}{.00306}, \sigma_{u\eta} = \underset{(1.82\times10^{-5})}{-4.43 \times 10^{-5}}. \end{aligned} \tag{21}$$

Suppose that the investor uses a simple linear portfolio rule to time the portfolio weight in the stock market portfolio relative to the risk-free asset. Let the stock weight, denoted by α_t, be linearly related to the current equity premium:

$$\alpha_t = \alpha_0 + \alpha_1(x_t - \mu). \tag{22}$$

Campbell and Viceira (1999) show that this form for the portfolio rule is approximately optimal given the assumptions we have made. They also solve for the optimal coefficients α_0 and α_1 as functions of the underlying parameters of the model, but here we treat α_0 and α_1 as free parameters.

Denote the portfolio return generated by the market-timing policy (22) by r_* and denote the cash-flow and discount-rate news computed with respect to this portfolio strategy by N_{CF*} and N_{DR*}. The long-horizon investor's first-order condition states that

$$\begin{aligned} \mathrm{E}_t[r_{i,t+1}] - r_{rf,t+1} + \frac{\sigma_{i,t}^2}{2} &= \gamma \mathrm{Cov}_t(r_{i,t+1}, N_{CF*,t+1}) + \mathrm{Cov}_t(r_{i,t+1}, -N_{DR*,t+1}) \quad (23) \\ &= \gamma \sigma_{*,t}^2 \beta_{i,CF*,t} + \sigma_{*,t}^2 \beta_{i,DR*,t}, \end{aligned}$$

where the news terms are computed relative to the portfolio strategy determined by (22). The cash-flow and discount-rate news in the first-order condition (23) correspond to news about the returns on this strategy.

Since the portfolio weight in stocks is time varying, the news formulas need to incorporate not only the change in expected excess market returns but also the change in expected allocation to stocks. If returns are generated by (20) with homoskedastic shocks, and if the investor follows the portfolio policy (22), the expected excess portfolio return is

$$\mathrm{E}_t(r_{p,t+1}) - r_{rf} = c_1 + c_2 \widetilde{x}_t + c_3 \widetilde{x}_t^2 \quad (24)$$

and the discount-rate news is

$$N_{DR*} = -\left(\frac{\rho}{1-\rho\phi^2} c_3\right) \sigma_\eta^2 + \left(\frac{\rho}{1-\rho\phi} c_2\right) \eta_{t+1} + \left(\frac{\rho}{1-\rho\phi^2} c_3\right) (2\eta_{t+1} \widetilde{x}_t^2 + \eta_{t+1}^2). \quad (25)$$

Here $\widetilde{x}_t \equiv x_t - \mu$, $c_1 \equiv \alpha_0 \mu + \frac{1}{2}\sigma_u^2(\alpha_0 - \alpha_0^2)$, $c_2 \equiv \alpha_0 + \alpha_1 \mu + \frac{1}{2}\sigma_u^2 \alpha_1$, and $c_3 \equiv \alpha_1 + \frac{1}{2}\sigma_u^2 \alpha_1^2$. Derivations of (24) and (25) are available from the authors on request. Cash-flow news can then be solved from the realized portfolio return, beginning-of-period expected return, and discount-rate news.

For our empirical tests, we use a modified, unconditional version of the first-order condition (23). We use excess returns with a time-varying exposure, $\alpha_t(R_{i,t+1} - R_{rf,t+1})$, on the left-hand side, where α_t is the investor's equity allocation determined by (22). We also take unconditional expectations of (23) to derive the unconditional version:

$$\mathrm{E}[\alpha_t(R_{i,t+1} - R_{rf,t+1})] = \gamma \sigma_*^2 \beta_{i,CF*} + \sigma_M^2 \beta_{i,DR*} \quad (26)$$

Two features of (26) that separate this equation from (15) are worth noting. First, the cash-flow and discount-rate betas are now computed relative to the market-timing portfolio. Second, the left-hand side returns are scaled with the investor's stock weight. Essentially, the question we are asking is whether the investor would be better off having a constant over- or underweight as a fraction of her stock holdings in some of the test assets.

In Table 13, each row corresponds to a value for average stock weight (α_0) and each column to aggressiveness of the timing policy (α_1). The cells of the table show the value of relative risk aversion implied by the cross-sectional premia estimates ($\widehat{g}_1/\widehat{g}_2$) and the estimated cross-sectional R^2, both from (16). All tests use the full asset set (both the characteristics-sorted and risk-sorted portfolios) and constrain the zero-beta rate to equal the T-bill rate. The basic message from Table 13 is that, as long as the average equity weight is high enough and the timing policy is not too aggressive, the cross-section of average returns appears to line up well with the predictions of the first-order condition (26). The performance of the model is weakest for aggressive market timing rules and low average stock weights in the post-1963 subperiod.

Are the risk-aversion coefficients reported in Table 13 reasonable, in the light of average stock weight and aggressiveness of the timing coefficient? We have made an attempt to quantify the link between the cross-sectional estimate of risk aversion and the investor's market-timing rule. Under the assumption that returns are generated by (20) and that the investor has the Epstein-Zin objective function (11), Campbell and Viceira (1999) show that the optimal portfolio weight in stocks is linearly related to the current equity premium:

$$\alpha_t = \alpha_0^{CV} + \alpha_1^{CV}(x_t - \mu). \tag{27}$$

Furthermore, Campbell and Viceira show how to solve the parameters of the optimal portfolio rule, α_0^{CV} and α_1^{CV}, as functions of γ, ψ, δ, μ, ϕ, σ_u^2, σ_η^2, $\sigma_{u\eta}$, and $\overline{r}_f$ (the constant log risk-free rate). Our attempts to reconcile the cross-sectional risk-aversion estimates, Campbell and Viceira's optimal timing rule, and the cross-sectional first-order condition (26) have been unsuccessful. The difficulty arises from the fact that the Campbell-Viceira rule implies perhaps unrealistically variable portfolio weights for low γ values ($\gamma = 2, \delta = \rho = .95^{1/12}, \overline{r}_{rf} = .015/12 \Longrightarrow \alpha_1^{CV} = 219$), and very low average stock allocation for high values of γ ($\gamma = 40, \delta = \rho = .95^{1/12}, \overline{r}_{rf} = .015/12 \Longrightarrow \alpha_0^{CV} = .15$).

Table 13: First-order condition of a strategic asset allocator

The table shows the estimated risk-aversion coefficient γ and cross-sectional R^2 obtained using a market-timing investor's first-order condition. The investor is assumed to allocate α_t fraction of her wealth to stocks, where $\alpha_t = \alpha_0 + \alpha_1(x_t - \mu)$ and $x_t - \mu$ is the deviation of the conditional equity premium from its unconditional mean. The heading of each panel corresponds to the sample period. Test assets are the 24 ME and BE/ME portfolios and 20 risk-sorted portfolios. The zero-beta rate is constrained to equal the T-bill rate.

1929:1-2001:12

$(\widehat{\gamma}, \widehat{R}^2)$	$\alpha_1 = 0$		$\alpha_1 = 1$		$\alpha_1 = 5$		$\alpha_1 = 10$		$\alpha_1 = 20$	
$\alpha_0 = .4$	21.6	59%	22.0	59%	24.1	57%	27.2	43%	33.8	-76%
$\alpha_0 = .6$	13.0	57%	13.1	57%	13.9	58%	14.9	56%	17.4	36%
$\alpha_0 = .8$	8.7	55%	8.8	55%	9.1	56%	9.5	57%	10.6	53%
$\alpha_0 = 1.0$	6.1	51%	6.1	51%	6.3	53%	6.5	54%	7.0	55%
$\alpha_0 = 1.2$	4.4	48%	4.4	48%	4.5	49%	4.6	50%	4.8	52%
$\alpha_0 = 1.4$	3.2	43%	3.2	43%	3.2	44%	3.2	45%	3.3	46%

1929:1-1963:6

$(\widehat{\gamma}, \widehat{R}^2)$	$\alpha_1 = 0$		$\alpha_1 = 1$		$\alpha_1 = 5$		$\alpha_1 = 10$		$\alpha_1 = 20$	
$\alpha_0 = .4$	13.3	44%	13.3	43%	13.2	38%	13.0	31%	12.6	13%
$\alpha_0 = .6$	7.8	44%	7.8	44%	7.7	42%	7.6	38%	7.3	31%
$\alpha_0 = .8$	5.1	45%	5.1	45%	5.0	43%	4.9	42%	4.7	38%
$\alpha_0 = 1.0$	3.4	45%	3.4	45%	3.3	44%	3.3	43%	3.1	41%
$\alpha_0 = 1.2$	2.3	45%	2.3	45%	2.3	45%	2.2	44%	2.0	43%
$\alpha_0 = 1.4$	1.6	45%	1.5	45%	1.5	45%	1.4	45%	1.3	44%

1963:7-2001:12

$(\widehat{\gamma}, \widehat{R}^2)$	$\alpha_1 = 0$		$\alpha_1 = 1$		$\alpha_1 = 5$		$\alpha_1 = 10$		$\alpha_1 = 20$	
$\alpha_0 = .4$	75.0	20%	81.8	-50%	23.0	-684%	-28.4	-514%	-17.7	-273%
$\alpha_0 = .6$	47.1	37%	50.2	5%	44.5	-333%	-5.5	-597%	-14.6	-345%
$\alpha_0 = .8$	33.1	50%	34.9	34%	37.1	-131%	13.6	-462%	-10.0	-391%
$\alpha_0 = 1.0$	24.7	60%	25.8	52%	28.7	-31%	20.6	-264%	-4.4	-390%
$\alpha_0 = 1.2$	19.1	66%	19.9	62%	22.4	22%	20.5	-115%	1.4	-334%
$\alpha_0 = 1.4$	15.1	68%	15.7	67%	17.7	51%	18.0	-22%	6.0	-238%

4.4 Loose ends and future directions

A number of unresolved issues remain. First, our model is silent on what is the ultimate source of variation in the market's discount rate. The mechanism that causes the market's overall valuation level to fluctuate would have to meet at least two criteria to be compatible with our simple intertemporal asset-pricing model. The shock to discount rates cannot be perfectly correlated with the shock to cash flows. Also, states of the world in which discount rates increase while expected cash flows remain constant should not be states in which marginal utility is unusually high for other reasons. If marginal utility is very high in those states, the discount-rate risk factor will have a high premium instead of the low premium we detect in the data.

Second, we have estimated the cash-flow and discount-rate betas of value and growth stocks from the behavior of their returns, without showing how these betas are linked to the underlying cash flows of value and growth companies. Similar to our decomposition of the market return, an individual firm's stock return can be split into cash-flow and discount-rate news. Through this decomposition, a stock's cash-flow and discount-rate betas can be further decomposed into two parts each, along the lines of Campbell and Mei (1993) and Vuolteenaho (2002), and this decomposition might yield interesting additional insights. For example, our equity-dependence hypothesis predicts that at least some of the high covariance between growth stocks' returns and the market's discount-rate news is due to covariance between growth stocks' cash flows and the market's discount-rate news. A pure investor-sentiment hypothesis would probably predict that all of the higher discount-rate beta is due to covariance between growth stocks' expected returns and the market's discount-rate news.

Third, we have nothing to say about the profitability of momentum strategies. Although we have not examined this issue in detail, we remain pessimistic about the two-beta model's ability to explain average returns on portfolios formed on past one-year stock returns, or on recent earning surprises. Stocks with positive past news and high short-term expected returns are likely to have a higher fraction of their betas due to discount-rate betas, and thus are likely to have even lower return predictions in the ICAPM than the already-too-low predictions of the static CAPM.

5 Conclusions

In his discussion of empirical evidence on market efficiency, Fama (1991) writes: "*In the end, I think we can hope for a coherent story that (1) relates the cross-section properties of expected returns to the variation of expected returns through time, and (2) relates the behavior of expected returns to the real economy in a rather detailed way.*" In this paper, we have presented a model that meets the first of Fama's objectives and shows empirically that Merton's (1973) intertemporal asset pricing theory helps to explain the cross-section of average stock returns.

We propose a simple and intuitive two-beta model that captures a stock's risk in two risk loadings, cash-flow beta and discount-rate beta. The return on the market portfolio can be split into two components, one reflecting news about the market's future cash flows and another reflecting news about the market's discount rates. A stock's cash-flow beta measures the stock's return covariance with the former component and its discount-rate beta its return covariance with the latter component. Intertemporal asset pricing theory suggests that the "bad" cash-flow beta should have a higher price of risk than the "good" discount-rate beta. Specifically, the ratio of the two risk prices should equal the risk aversion coefficient of a representative investor, and the "good" risk price should equal the variance of the return on the market.

Empirically, we find that value stocks and small stocks have considerably higher cash-flow betas than growth stocks and large stocks, and this can explain their higher average returns. The post-1963 negative CAPM alphas of growth stocks are explained by the fact that their betas are predominantly of the good variety. The model also explains why the sort on past CAPM betas induces a strong spread in average returns during the pre-1963 sample but little spread during the post-1963 sample. The post-1963 CAPM beta sort induces a post-ranking spread only in the good discount-rate beta, which carries a low premium. Finally, the model achieves these successes with the discount-rate premium constrained to the prediction of the intertemporal model.

Our two-beta model is, of course, not the first attempt to operationalize Merton's (1973) intertemporal CAPM. However, we hope that our model is an improvement over the specifications by Campbell (1996), Li (1997), Hodrick, Ng, and Sengmueller (1999), Lynch (1999), Chen (2000), Brennan, Wang, and Xia (2001), Ng (2002), Guo (2002), and others in two respects. First, our specification "works" in the sense that it has respectable explanatory power in explaining the cross-section of average asset returns with premia restricted to values predicted by the theory. Second, by restating the model in the simple two-beta form, with a close link to the static CAPM, we hope to facilitate the empirical implementation of the ICAPM in both academic research and practical industry applications.

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