Long-Run Cash-Flow and Discount-Rate Risks in the Cross-Section of US Returns*

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Abstract

This paper decomposes the overall market beta of common stocks into four parts reflecting uncertainty related to the long-run dynamics of stock-specific and market-wide cash flows and discount rates. We employ a discrete time version of Merton's Intertemporal CAPM to test whether these four sources of risk command different risk prices. The model performs well in pricing average returns on single- and double-sorted portfolios according to size, book-to-market, dividend-price ratios and past risk. It generates high estimates for the explained cross-sectional variation in average returns, lower average pricing errors than the Fama-French three factor model and economically and statistically acceptable estimates for the coefficient of relative risk aversion.

JEL: G11, G12, G14

Keywords: CAPM, cash-flow risk, discount-rate risk, asset pricing

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1 Introduction

Since the original statement of the Sharpe (1964)-Lintner (1965) static Capital Asset Pricing Model (CAPM), there is a considerable ongoing debate on whether its single risk measure, the market beta, can adequately describe the cross-section of average returns on individual stocks and portfolios sorted according to risk measures and firm-specific characteristics. Numerous studies have shown that the CAPM, at least in its unconditional form, performs poorly in explaining the cross-sectional variation of mean excess returns.[1] In a recent paper, Campbell, Polk and Vuolteenaho (2005) decompose the total market beta of common stocks into four components related to the covariance of unexpected changes in stock-specific cash flows and discount rates with unexpected changes in market-wide cash flows and discount rates. In this paper, we empirically test whether these four sources of risk are priced using a discrete time version of Merton's (1973) Intertemporal Capital Asset Pricing Model (I-CAPM).

Our study is closely related to a number of papers trying to identify long-run risks that could match the observed premia on various classes of assets. In a novel paper, Campbell (1991) shows that unexpected stock returns can be decomposed into the discounted sum of revisions in expectations about future cash flows and future discount rates. Campbell and Mei (1993) extend this analysis by studying the behavior of asset-specific cash-flow and discount-rate components of portfolio betas but do not provide any evidence on whether these parts of systematic risk carry individual risk prices. Bansal and Yaron (2003) and Bansal, Dittmar and Lundblad (2005) study the behaviour of dividends and aggregate consumption in a Consumption-CAPM (C-CAPM) and show that the exposure of dividends to changes in aggregate consumption (dividend-consumption beta) could match a large proportion of the cross-sectional spread of returns. Santos and Veronesi (2005) study the temporal behaviour of value stock returns and show that value stocks have higher cash-flow risk and moreover, the size of the value premium is increasing in relatively bad times due to variation in risk preferences through time. Hansen, Heaton and Li (2005) show that growth stocks have low long-run cash-flow covariation with consumption relative to value stocks and Parker and Julliard (2005) argue that the simple C-CAPM can match the cross-sectional distribution

[1] For a recent review on the CAPM see, among others, Fama and French (2004).

of excess returns when consumption risk is measured over the long-run. Da (2005) argues that a cash-flow beta along with a cash-flow duration beta can significantly increase the ability of the C-CAPM to explain the value premium. Finally, Bakshi and Chen (2005) show that compensations for cash flow risk and discounting risk could solve the aggregate equity premium puzzle of Mehra and Prescott (1985).

Our work is most closely related to Campbell and Vuolteenaho (2004) and Campbell, Polk and Vuolteenaho (2005). Campbell and Vuolteenaho (2004) show that the total market CAPM beta can be decomposed into a relatively "bad" market cash-flow beta, reflecting risk related to news about the market's future dividends, and a relatively "good" market discount rate beta, reflecting risk related to news about the market's future excess returns. They argue that the two components of total market risk have different implications for the rational investor. Since shocks to market cash flows and market discount rates represent permanent and temporary shocks to overall wealth respectively, conservative investors are particularly averse to the former and require a premium which is a multiple of their attitude towards risk. As a result, discount rate betas are relatively "good" betas with low risk prices, whereas cash flow betas are "bad" betas with high risk prices. Empirically, Campbell and Vuolteenaho (2004) find that small stocks and value stocks have considerably higher cash-flow ("bad") betas than growth stocks and large stocks, and this can explain their higher average returns. However, they restrict their analysis by assuming that "good" and "bad" betas are independent of whether the innovation in individual returns is due to unexpected changes in future cash-flows or discount rates of the company (see, also, Daniel and Titman. 2005).

More recently, Campbell, Polk and Vuolteenaho (2005) decompose the overall market beta into four betas, which reflect the covariance of unexpected changes in stock-specific cash flows and discount rates with unexpected changes in market-wide cash flows and discount rates. This decomposition of the market beta allows to answer the question whether the high "bad" beta of small and value stocks and the high "good" beta of growth stocks and large stocks are attributable to their cash flows or their discount rates. They estimate sample betas for 5 deciles of book-to-market sorted (growth-value) portfolios and show that growth portfolios' cash flows are particularly sensitive to temporary movements in aggregate stock prices (driven by market-wide shocks to discount rates) while value portfolios' cash-flows are highly correlated with temporary movements in market returns (driven by market-wide shocks to cash-flows). However, they do not study the four-beta decomposition of portfolios sorted on size (or other characteristics) and, more importantly, do not test the asset pricing implications of this four factor model thus leaving the question unanswered as to what economic forces determine the risk prices associated with these four sources of risk.

The present study extends Campbell, Polk and Vuolteenaho (2005) in three important respects: First, we relax the assumption of homoskedasticity of excess returns and compute risk-adjusted news about future cash flows and discount rates by controlling with the conditional volatility of returns and information variables which have predictive ability for future returns. Formally, we use a VAR-GARCH model to estimate news instead of a VAR model. Our proposed method of controlling for conditional volatility is equivalent to assuming that investors put a lower weight to information originating from more volatile state variables when they update their forecasts about future returns and cash flows. It turns out that accounting for volatility can control for structural breaks in the exposure of value and growth stocks to cash-flow and discount-rate risks. In particular, we find that the spread in the discount rate "bad" beta between value and growth stocks does not change significantly after 1963, contradicting evidence presented in Campbell and Vuolteenaho (2004). Second, we extend the analysis of Campbell, Polk and Vuolteenaho (2005) to size-sorted portfolios and ask whether long-run cash-flow and discount-rate risks can account for the size premium, i.e. the higher average return of small stocks relative to large stocks, and we find that it does. Third, we test whether the four components of the overall market beta are priced in the cross-section of stock returns according to a discrete version of Merton's (1973) I-CAPM that identifies changes in expectations about future dividend growth and future risk premia as long-run risk factors.

Overall, we find that the four-beta model shows considerable in-sample success in pricing monthly average returns over the period from December 1928 to December 2001. The model generates insignificant average pricing errors (which are much smaller compared to the popular Fama-French (1993) three-factor model), high estimates for the explained cross-sectional variation in average returns and statistically and economically acceptable estimates for the degree of relative risk aversion. Furthermore, we find that permanent shocks to market returns are the main determinant of the overall risk premium and their covariances with both portfolio cash-flow and discount-rate shocks earn equilibrium risk premia that are distinguishable from zero, but the premia associated with asset-specific dividend-growth news are greater than those linked to asset-specific future return news. More importantly, we provide evidence that, as predicted by economic theory, the coefficient of proportionality between the two premia is equal to the constant coefficient of relative risk aversion.

The remainder of the paper is as follows: Section 2 provides the theoretical decomposition of total market risk into four parts: cash-flow and discount-rate portfolio risks associated with market's cash-flow and discount-rate dynamics. Also, it develops the asset pricing framework that will be used for estimation. Section 3 describes the data and the econometric model used to extract the news components of unexpected returns. Section 4 reports the empirical results and Section 5 concludes.

2 Decomposing Risk and Return

2.1 Cash-Flow and Discount-Rate Risk

The starting point of our analysis is the decomposition of the unexpected return, developed by Campbell and Shiller (1988a, 1988b) and further expanded by Campbell (1991). We define the one-period holding real gross return on asset i as $r_{i,t+1} = \log(P_{i,t+1} + D_{i,t+1}) - \log(P_{i,t})$, where $P_{i,t+1}$ is the real stock price measured at the end of period $t+1$ (ex-dividend) and $D_{i,t+1}$ is the real dividend payment during this period. Approximating this return with a first-order Taylor expansion around the, assumed constant, mean log dividend-price ratio, $\overline{\delta_i} = E[\log(d_{i,t} - p_{i,t})]$, we obtain:

$$r_{i,t+1} \approx k_i + \rho_i p_{i,t+1} - p_{i,t} + (1-\rho_i) d_{i,t+1}, \tag{1}$$

with $k_i = -\log(\rho_i) - (1-\rho_i)\log[(1/\rho_i) - 1]$, and $\rho_i = 1/[1 + \exp(\overline{\delta_i})]$ being firm-specific constants. Campbell (1991), using this approximation of log returns, goes one step further and derives a decomposition of the unexpected return, $e_{i,t+1} = r_{i,t+1} - E_t\left[r_{i,t+1}\right]$, into revisions in expectations about future dividend growth rates (that is, growth rates of future cash flows) and revisions in expectations about future log returns (that is, future discount rates):

$$e_{i,t+1} = N^C_{i,t+1} - N^D_{i,t+1}, \tag{2}$$

where $N^C_{i,t+1}$ and $N^D_{i,t+1}$ are defined as $N^C_{i,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho_i^j \Delta d_{i,t+1+j}$ and $N^D_{i,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho_i^j r_{i,t+1+j}$, respectively, and $(E_{t+1} - E_t)\, x_{t+1+j} \equiv E_{t+1}[x_{t+1+j}] - E_t[x_{t+1+j}]$ is the time $t+1$ revision in expectations operator.

The above sums can be viewed as representing cash-flow and discount-rate "news" for the investor, since any upward or downward revision in her expectations at time $t+1$ (relative to the expectation at time t) should be consistent with the arrival of new valuable information at time $t+1$. Moreover, as Campbell and Shiller (1988a), and Campbell (1991) argue, equation (2) must be considered as a consistent model of expectations since a positive (negative) unexpected return today must be only associated with an upward (downward) revision in expectations about future cash-flows, a downward (upward) revision in expectations about future returns, or a combination of the two. That is, although equation (2) does not restrict the generating mechanism of expectations or the asset pricing model that derives equilibrium expected returns, it restricts the way through which changing expectations due to "good" or "bad" news affect unexpected returns on any asset if investors' expectations are to be consistent with the observed asset prices.

The two components of unexpected returns in (2) can be viewed as permanent and transitory shocks to the value of the underlying asset. A positive unexpected return caused by an upward revision in cash-flow expectations represents a permanent positive effect on the value of the asset since it is never reversed subsequently, whereas a positive unexpected return generated from a downward revision in expectations about future returns can be viewed as a temporary shock to the asset price, since the capital gain today is at a cost of lower future investment opportunities. In the case where the underlying asset is the total wealth portfolio held by investors, these effects can be viewed as permanent and temporary movements in total wealth.

We now turn to link the sources of time variation in asset returns with the associated sources in the total wealth portfolio. Following Campbell and Mei (1993), we define the "market" or CAPM beta as the ratio of the conditional covariance of asset's and market's unexpected returns divided by the conditional variance of market unexpected returns:

$$\beta_{im,t} = \frac{Cov_t\left(e_{i,t+1}, e_{m,t+1}\right)}{Var_t(e_{m,t+1})}, \tag{3}$$

where $Var_t(.)$ and $Cov_t(.)$ are the conditional, at time t, variance and covariance operators, respectively. Given that the current innovation in returns on both the asset i and the market portfolio m can be written as the sum of cash-flow and (the negative of) discount-rate news (equation (2)), we obtain the following decomposition of the conditional market sensitivity $\beta_{im,t}$ which can be now written as the sum of four conditional "beta-like measures" of total market systematic risk:

$$\begin{aligned}
\beta_{im,t} &= \frac{Cov_t(N^C_{i,t+1} - N^D_{i,t+1}, N^C_{m,t+1} - N^D_{m,t+1})}{Var_t(e_{m,t+1})} \\
&= \beta_{i,CC,t} + \beta_{i,CD,t} + \beta_{i,DC,t} + \beta_{i,DD,t},
\end{aligned} \tag{4}$$

where the individual components of total market risk, $\beta_{i,CC,t}, \beta_{i,CD,t}, \beta_{i,DC,t}$, and $\beta_{i,DD,t}$, are defined as:

$$\beta_{i,CC,t} = \frac{Cov_t(N^C_{i,t+1}, N^C_{m,t+1})}{Var_t(e_{m,t+1})}, \qquad \beta_{i,CD,t} = \frac{Cov_t(N^C_{i,t+1}, -N^D_{m,t+1})}{Var_t(e_{m,t+1})},$$

and

$$\beta_{i,DC,t} = \frac{Cov_t(-N^D_{i,t+1}, N^C_{m,t+1})}{Var_t(e_{m,t+1})}, \qquad \beta_{i,DD,t} = \frac{Cov_t(-N^D_{i,t+1}, -N^D_{m,t+1})}{Var_t(e_{m,t+1})} \tag{5}$$

The "beta-like" ratios in (5) are not the traditional conditional sensitivities used in APT models. These models identify betas to be equal to the univariate slope coefficient of a regression of unexpected asset returns on the unexpected component of the risk factor or the unexpected return of a factor mimicking portfolio if the factor is a traded asset. Rather, the "beta-like" measures of systematic risk in (5) represent the part of total market (CAPM) risk attributed to portfolio and market shocks to time-varying economic fundamentals (cash-flows, N^C_i and N^C_m) and shocks to time-varying returns (discount-rates, N^D_i and N^D_m). Thus, this decomposition allows us to study the properties of the total CAPM betas' components and to ask whether these parts of systematic risk command different equilibrium risk prices.

2.2 Pricing cash-flow and discount-rate risk

In order to derive testable restrictions on the premia associated with the cash-flow and discount rate risks in (4), we need a risk story. For this purpose, we employ the recursive utility framework provided by Epstein and Zin (1989, 1991) and Weil (1989). The lifetime utility function of the investor is given by the recursive utility function U_t, defined over current real consumption and future expected utility of real consumption:

$$U_t\left[C_t, E_t\left(U_{t+1}\right)\right] = \left[(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta E_t\left(U_{t+1}^{1-\gamma}\right)^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{6}$$

where C_t is current real consumption at time t, $0 < \delta < 1$ is the subjective discount factor, $\gamma > 0$ is the constant coefficient of relative risk aversion (CRRA), θ is a parameter defined as $\theta = (1-\gamma)/(1-\sigma^{-1})$, and $\sigma > 0$ is the elasticity of intertemporal substitution (EIS) between current and expected future consumption. Equation (6) has the advantage of breaking the tight link between CRRA and EIS given by power utility ($\gamma = \sigma^{-1}$), thus, disconnecting investors' risk attitude across states of nature and across time.[2] The consumer is assumed to finance all her consumption plan entirely from her total real wealth W_t, given the following dynamic budget constraint:

$$W_{t+1} = (1 + R_{m,t+1})(W_t - C_t), \tag{7}$$

where $R_{m,t+1}$ is the net real return on total wealth (or the market portfolio, m). Epstein and Zin (1989) solve for the optimal portfolio and consumption policies and show that the following set of conditional moment restrictions hold for each asset i:

$$E_t\left[\beta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\sigma}}(1 + R_{m,t+1})^{\theta-1}(1 + R_{i,t+1})\right] = 1 \tag{8}$$

[2] For a discussion of the properties of this specification see Campbell (2003) and the references therein.

The above set of non-linear moment restrictions can be linearized using the assumption of joint conditional log-normality of asset returns and consumption in the spirit of Hansen and Singleton (1983). Campbell (1993, 1996) goes one step further and, using these strong assumptions along with the dynamic budget constraint in (7), derives the following cross-sectional linear restrictions on assets' risk premia:[3]

$$E_t\left[R^e_{i,t+1}\right] = \gamma Cov_t(e_{i,t+1}, e_{m,t+1}) + (\gamma - 1)\, Cov_t(e_{i,t+1}, N^D_{m,t+1}), \tag{9}$$

which using equation (2) for any individual asset as well as the market portfolio, m, gives:

$$\begin{aligned} E_t\left[R_{i,t+1}\right] &= \gamma Cov_t(N^C_{i,t+1}, N^C_{m,t+1}) + Cov_t(N^C_{i,t+1}, -N^D_{m,t+1}) \\ &\quad + \gamma Cov_t(-N^D_{m,t+1}, N^C_{m,t+1}) + Cov_t(-N^D_{i,t+1}, -N^D_{m,t+1}) \end{aligned} \tag{10}$$

The left part of equations (9) and (10) represents the risk premium in simple returns which, in log form, is equivalent to $E_t\left[r_{i,t+1}\right] - r_{f,t+1} + \frac{1}{2} Var_t\left(e_{i,t+1}\right)$. The covariance-risk representation of the equity premium in (10) can be rewritten in terms of a "beta-like-premium" representation (see, for example, Cochrane, 2001). Multiplying and dividing each conditional covariance term in (10) by the conditional variance of market's unexpected returns, $\mathrm{Var}_t(e_{m,t+1})$, we obtain the following representation for the risk premium of asset i:

$$E_t\left[R^e_{i,t+1}\right] = \lambda_{0,t} + \lambda_{CC,t}\beta_{i,CC,t} + \lambda_{CD,t}\beta_{i,CD,t} + \lambda_{DC,t}\beta_{i,DC,t} + \lambda_{DD,t}\beta_{i,DD,t}, \tag{11}$$

where $\lambda_{0,t}$ represents the conditional Jensen's alpha, the rest of the λs represent time-varying prices of beta risks, defined as $\lambda_{CC,t} = \lambda_{DC,t} = \gamma Var_t(e_{m,t+1})$ and $\lambda_{CD,t} = \lambda_{DD,t} = Var_t(e_{m,t+1})$, respectively, and the betas are defined similarly to (5). Equation (11) states that the required risk premium on asset i is jointly determined by the covariances of asset-specific shocks to cash flows and discount rates with market-wide shocks to cash flows and discount rates. Similarly to Campbell and Vuolteenaho (2004), a conservative risk-averse investor with $\gamma > 1$ demands a higher risk price for risks associated with market-wide cash-

[3] Campbell (1993, 1996) and Guo (2005) discuss how to handle heteroscedasticity of returns. Equation (8) approximately holds even if returns are heteroskedastic if one assumes that the elasticity of intertemporal substitution is equal to unity. Since our aim is to test the unconditional version of our the model, we employ this assumption.

flow uncertainty ($\beta_{i,CC,t}$ and $\beta_{i,DC,t}$) rather than for risks linked to shocks to market returns ($\beta_{i,CD,t}$ and $\beta_{i,DD,t}$), since any positive (negative) shock to market discount rates is at a benefit (cost) of worse future investment opportunities, whereas the investor is never compensated later for every positive (negative) shock to dividends. Hence, the beta prices of market-related cash-flow risk, λ_{CC} and λ_{DC}, are a γ multiple of the beta risk prices of market discount-rate risk, λ_{CD} and λ_{DD}, respectively.

We are interested in studying average portfolio returns for a long sample of U.S. stock market and macroeconomic data in order to get comparable results to the literature of the unconditional CAPM and, more importantly, to the empirical findings of the two-beta model of Campbell and Vuolteenaho (2004). Using the methodology described in the next section, we proceed with an unconditional version of (11):

$$E\left[R^e_{i,t+1}\right] = \lambda_0 + \lambda_{CC}\beta_{i,CC} + \lambda_{CD}\beta_{i,CD} + \lambda_{DC}\beta_{i,DC} + \lambda_{DD}\beta_{i,DD} \tag{12}$$

3 Data and Empirical Methodology

We study monthly US asset and macroeconomic data from December 1928 to December 2001 (877 monthly observations). Our data consist of different sets of common stock portfolios sorted on various firm-specific characteristics and risk measures, and a set of economy-wide variables that serve as instruments. Following common practice, these variables have been selected under the assumption that they forecast future returns.

The test assets include (a) the 25 size-BE/ME sorted portfolios from CRSP, corresponding to the Davis, Fama and French (2000) data file, (b) the 20 risk-sorted portfolios provided by Campbell and Vuolteenaho (2004),[4] and (c) a set of 10 book-to-market, 10 dividend-price ratio and 10 size sorted portfolios (30 in total). The value-weighted CRSP portfolio serves as the market portfolio of all traded wealth.[5] Although our model in (12) is written in real log

[4] Campbell and Vuolteenaho (2004) sort common stocks into 20 portfolios according to their past loadings on the market return and innovations on the VAR state variables. The purpose of their strategy is to generate portfolios with large spread in these loadings and thus overcome Daniel and Titman's (1997) observation that sorting only on firm characteristics could generate a spurious link between premia and risk measures.

[5] The returns on book-to-market, size and dividend-price sorted portfolios, as well as on the Fama-French (1993) aggregate book-to-market and size factor mimicking portfolios (HML a SMB) are taken from Kenneth's French web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

returns, we assume that for the monthly test interval we employ, inflation rates are almost fully forecastable, and thus we proxy real log returns with nominal log returns.

Following common practice, we use the following variables that have been successful in predicting the future state of the economy and asset returns: (a) the log excess market return $r_m - r_f$, defined as the difference between the log return on the value-weighted CRSP stock index portfolio and the log return on the risk-free rate, constructed by CRSP from T-bills with approximately 3 month maturity, (b) the log price-earnings ratio, $p - e$, taken from Shiller (2000) and defined as the log of the S&P 500 index, scaled by the 10-year moving average of aggregate earnings of companies in the S&P 500 index, (c) the term yield spread, TY, constructed by Global Financial Data and defined as the yield differential between ten-year taxable bonds and short-term taxable notes, and (d) the small-stock value spread, VS, defined as the difference between the log(BE/ME) of the small high-BE/ME portfolio and the log(BE/ME) of the small low-BE/ME portfolio.[6]

Measuring cash-flow news and discount-rate news as the main sources of risk is central in our methodology. We follow Campbell (1991) and estimate the cash-flow news and discount-rate news series using a first-order vector autoregressive (VAR) model. We first estimate expected returns and the revisions in expectations about future returns, $E_t\left[r_{t+1}\right]$ and $(E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho_i^j r_{t+1+j}$, respectively. This practice has an important advantage as it relies only on the dynamics of expected returns and there is no need for modelling the dynamics of dividends. The latter are derived by the VAR estimates and the realizations of returns and state variables.

We assume that the data are generated by the following VAR model:

$$Y_{t+1} = C + AY_t + U_{t+1}, \tag{13}$$

where $Y_{t+1} = (r_{i,t+1}, Y_{1,t+1}, ..., Y_{m,t+1})$ is a $m \times 1$ vector of variables containing returns as its first element and $(m-1)$ variables which have predictive power for returns, C is a $m \times 1$ vector of constants and A is a $m \times m$ matrix of constants.

[6]The returns on the 20 risk sorted portfolios and the state variabes $r_m - r_f, TY$ and VS have been kindly provided by Tuomo Vuolteenaho and correspond to those used in Cambell and Vuolteenaho (2004). For a recent work that examines the role of the value pread as a predictor of stock returns see Liu and Zhangy (2005).

Campbell and Vuolteenaho (2004) and Campbell, Polk and Vuolteenaho (2005) assume that innovations to returns and state variables have constant variance. Given mounting evidence of time-varying conditional volatility in asset returns, we relax this assumption and allow for heteroskedasticity of the VAR residuals. In particular, we assume that the $m \times 1$ error vector U_t is given by:

$$U_t = H_t^{1/2} z_t, \; z_t \sim \text{i.i.d.}(0, I_m), \tag{14}$$

where H_t is the conditional covariance matrix and the innovations sequence $\{z_t\}$ follows an m-variate standard Gaussian distribution. The conditional covariance matrix, H_t, is specified as a first-order diagonal BEKK model as suggested by Engle and Kroner (1995):

$$H_t = D'D + MU_{t-1}U'_{t-1}M' + GH_{t-1}G', \tag{15}$$

where D is a lower triangular $m \times m$ matrix of constant parameters and M and G are diagonal $m \times m$ matrices of constant parameters. Provided that the data are generated by the process as specified in equations (13)-(15), the standardized residuals vector:

$$z_t = \frac{U_t}{H_t^{1/2}} \sim \text{i.i.d.}(0, I_m)$$

has the property of a multivariate i.i.d. process. We estimate (13)-(15) for the market return and for each individual portfolio return. We then compute cash-flow and discount-rate news as linear functions of the $t+1$ vector of standardized innovations, z_{t+1}:

$$N_{t+1}^{D} = e1'\lambda z_{t+1} \text{ and } N_{t+1}^{C} = (e1' + e1'\lambda) z_{t+1}, \tag{16}$$

where $e1$ is a $m \times 1$ vector with the first element equal to unity and the remaining elements equal to zero. The mapping of the standardized shock vector to the news vectors is given by $\lambda \equiv \rho A(I_m - \rho A)^{-1}$. The term $e1'\lambda$ in (16) captures the long-run effect 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 A), 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 $(I_m - \rho A)^{-1}$. Since we use standardized residuals to compute news, the forecasting ability of each economic variable is filtered through the conditional variability derived from the GARCH(1,1) model. As a result, shocks to state variables that are expected to be volatile in the future have high conditional volatility and, hence, are of less importance in the construction of "news" series since the investor judges that these variables are less informative as predictive instruments.

A series of recent papers (see, for example, Chen, 2003, Ang, Hodrick, Xing and Zhang, 2004 and Ang, Chen and Xing, 2005) show that the exposure of assets to time-varying market volatility is priced in the cross section. Similarly to these papers, we relax the assumption of homoskedastic returns. However, our approach differs from the above papers in that we correct for the effect of time-varying volatility in the construction of cash-flow and discount-rate news by dividing the innovation terms with their conditional volatility instead of pricing volatility itself as an aggregate risk factor.

4 Empirical Evidence

4.1 Estimation of News Components for Market Portfolio

Table 1 reports parameter estimates for the market VAR model. Our estimates suggest that the state variables have some predictive power for stock market excess returns. Specifically, monthly market returns display some degree of reversal towards their mean with a statistically significant coefficient of 0.093. The effect of the term yield spread on market returns is positive and significant, a finding consistent with Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989) and Campbell and Vuolteenaho (2004). The remaining state variables, namely the log price-to-earnings ratio and the small-stock value spread, negatively predict the market return, confirming previous results by e.g. Campbell and Shiller (1988a, 1988b, 1998), Rozeff (1984), Fama and French (1988, 1989), Brennan, Wang and Xia (2001) and Eleswarapu and Reinganum (2004)). The remaining columns of Table 1 summarize the dynamics of the state variables. We do not comment on the remaining equations separately as our estimates coincide with those in Campbell and Vuolteenaho (2004). The last two rows of Table 1 report the ARCH-LM tests for heteroskedasticity in the VAR residuals. The statistics provide evidence for the existence of strong second-order dependence in the error terms.

[INSERT TABLE 1 HERE]

We model the second moments of the error vector U_t generated by the VAR model as GARCH (1,1) processes, i.e.,

$$h_{jt} = k_j + \mu_j^2 u_{jt-1}^2 + g_j^2 h_{jt-1} \tag{17}$$

where h_{jt}, $j = 1, ..., 4$, is the conditional variance of the j^{th} variable's innovations, u_{jt}, and k, μ, g are constant parameters. By accounting for time-varying volatility, we ensure that the distribution of the error vector U_t, conditional on its past history, is normal, or, equivalently, the standardized residuals of the GARCH (1,1) models, $z_{jt} = u_{jt}/\sqrt{h_{jt}}$, are normal. These normal and independent shocks are then fed into the mapping functions $e1'\lambda$ and $e1'+e1'\lambda$, to retrieve cash-flow and discount-rate news. Table 2 reports estimation results of the univariate GARCH(1,1) models for the error vector U_t. The GARCH parameter estimates (μ_j^2, g_j^2) are highly significant, with $\mu_j^2 + g_j^2 > 0.95$, suggesting strong volatility clustering and in some cases nearly integrated GARCH processes. The adequacy of the GARCH (1,1) model is supported by the LM test in the standardized residuals, reported in the last two rows of the table, which rejects any remaining second-order dependence.

[INSERT TABLE 2 HERE]

Table 3 summarizes the behavior of implied cash-flow news and discount-rate news components of market excess returns. The top panel shows that the standard deviation of discount rate news is twice the standard deviation of cash-flow news. This finding is consistent with Campbell (1991) and Campbell and Vuolteenaho (2004). The bottom panel of Table 3 reports correlations of cash-flow and discount-rate news with innovations in market excess returns and state variables. Discount-rate and cash-flow news are negatively correlated with innovations in the market excess return, the price-earnings ratio and the value spread. In contrast, innovations to the term spread are uncorrelated with discount-rate and cash-flow news.

[INSERT TABLE 3 HERE]

4.2 Estimation of Stock-Specific News Components and Betas

The VAR-GARCH methodology presented in Section 2 has been applied to every single portfolio under consideration, using the same economy-wide state variables, in order to extract portfolio-specific cash-flow and discount rate news. Since data on dividend yields of individual portfolios are not available to us, we follow Campbell and Mei (1993), and proxy individual discount factors, ρ_i in equation (2), with the full-sample estimate of the discount factor of the market portfolio, $\overline{\rho}_m = 0.9957$.[7]

The standardized innovations of the state variables are used to study the systematic risks and their relationship with average returns on portfolios of common stocks sorted on firm characteristics and risk. Empirical measures of the cash flow and discount rate betas in (4) are derived using a methodology similar to the one employed in Campbell and Vuolteenaho (2004) to ensure that our sample estimates are not affected by non-synchronous trading (especially in the early years of our 1928-2001 monthly sample) and under-reaction of stock prices to changes in the market index (especially for large stocks).[8] Our four sample betas, that will be used in the cross-sectional regressions, are defined as the "sum" of contemporaneous, one lag and two lags of the full-sample covariances of portfolio news at $t+1$ with market news, divided by the time $t+1$ full-sample estimate of the variance of standardized market return innovations, $\widehat{Var}(z_{m,t+1})$. For example, the betas associated with shocks to assets' cash-flows and revisions in market fundamentals in (5) are estimated as follows:

$$\widehat{\beta}_{i,CC} = \sum_{k=0}^{2} \frac{\widehat{Cov}(N_{i,t+1}^{C}, N_{m,t+1-k}^{C})}{\widehat{Var}(z_{m,t+1})}, \tag{18}$$

[7] We do not report the VAR(1) estimates for each of the individual portfolios. These results are available from the authors upon request.

[8] See Scholes and Williams (1977) and Dimson (1979) for the effects of non-synchronous trading and McQueen, Pinegar and Thorley (1996) and Peterson and Sanger (1995) for the under-reaction pattern of stock prices.

and all the remaining betas in (5) are estimated accordingly.

In addition to the use of standardized innovations, however, our method of estimating the betas in (18) differs from Campbell, Polk and Vuolteenaho (2005) in one important respect: While these authors estimate asset-specific discount-rate news from an asset-specific VAR where the state variables are portfolio-related attributes, we follow the advise of rational asset pricing theory and assume that both market and asset-specific returns are driven by a "common" set of economic variables. Hence, we use the same set of state variables in the VAR to forecast expected returns for all stocks. The innovations in these variables are then used as economy-wide risk factors in the cross-sectional asset pricing tests.[9]

Although intuitively appealing, our method of computing asset-specific news is subject to the criticism that the use of common state variables in the VAR introduces a high degree of correlation between asset-specific and market-wide discount-rate news. However, since the log return of the portfolio examined enters each portfolio VAR as the first variable (see, equations (13) and (16)) and the lagged portfolio return enters each predicting equation in the VAR, there is no reason to expect that the estimated innovations in the state variables (which in turn define the news series and the betas in (18)) are the same for each asset. In contrast, the estimated instrument innovations represent the unpredictable component of the istruments conditional on the lagged portfolio return. In addition, since the state variables usually explain a relatively low fraction of the variance of returns, news about future returns will be mainly determined by innovations in portfolio returns rather than by innovations in the state variables.

4.3 The Cross-Section of Cash-Flow and Discount-Rate Risks

Table 4 reports the estimated betas (as well as their standard errors in parentheses) given our definition in (18) for the 25 double sorted portfolios according to size and book-to-market. Campbell and Vuolteenaho (2004) find that the risk characteristics of value and growth stocks changed after 1963. Accordingly, in each panel of Table 4, we report on the left half the betas for the full sample period December 1928 - December 2001 and on the right half

[9] See e.g. Campbell (1993, 1996) who shows that if a state variable has predictive power for the overall market return, its innovations are priced in the cross-section of asset excess returns.

the betas for the period July 1963- December 2001. Before discussing the differences between the two samples, we report our main findings for the modern post-1963 sample.

[INSERT TABLE 4 HERE]

Six main results emerge from Table 4. First, as reported in Panel A, the CAPM betas show little cross-sectional variation, confirming the results of numerous previous studies that the single-factor CAPM fails to generate the spread in betas required to describe the cross-sectional differences in average returns.

Second, the observed spread in the two aggregate "bad" (cash-flow) and "good" (discount-rate) betas confirm the story of Campbell and Vuolteenaho (2004) that value stocks have relatively high bad betas while growth stocks have relatively high good betas – see Panels B and C of Table 4. The difference in cash-flow betas ($\beta_{i,C}$) between value and growth stocks – reported in the last column of Panel B, labelled "diff" – ranges from 0.034 for the smallest decile to 0.130 for the largest decile, while at the same time the difference in discount-rate betas ($\beta_{i,D}$) – reported in the last column of Panel C, labelled "diff" – ranges from -0.107 to -0.283.

Third, decomposing the CAPM beta into four betas can contribute significantly to understanding the value premium. All four betas, $\beta_{i,CC}$, $\beta_{i,CD}$, $\beta_{i,DC}$, and $\beta_{i,DD}$, show a remarkable spread across book-to-market sorted portfolios, as shown in Panels D-G of the table. The spread in the betas between value and growth stocks reported in the last column of Panels D to G is roughly one order of magnitude larger than in Campbell, Polk and Vuolteenaho (2005), suggesting that our method of filtering heteroskedasticity in news terms is able to uncover significant differences in betas across portfolios.

Fourth, $\beta_{i,CC}$ and $\beta_{i,DD}$ are positive for all stocks, suggesting that news about firms' cash flows are positively related to news about market cash flows and news about firms' discount rates are positively related to news about market discount rates. In sharp contrast, $\beta_{i,CD}$ and $\beta_{i,DC}$ are all negative, suggesting that good news about future discount rates (i.e. unexpected declines in future discount rates) are bad news about future cash flows. This observation is in line with the prediction of the standard C-CAPM that real interest rates are positively related to future economic activity.

Fifth, with the exception of the small decile, value stocks have both a larger cash-flow beta with respect to market cash flows, $\beta_{i,CC}$, than growth stocks and a larger discount-rate beta with respect to market discount rates, $\beta_{i,DD}$. Hence, value stocks are more risky than growth stocks because their cash flows are more sensitive to market cash-flow news and their discount rates are more sensitive to market discount-rate news. However, the net exposure of value stocks to changes in market discount rates, defined as $\beta_{i,D} = \beta_{i,DD} + \beta_{i,CD}$, is lower compared to growth stocks because their cash flows are more sensitive to changes in market discount rates, explaining the findings of Campbell and Vuolteenaho (2004) that value stocks have a relatively lower ("good") discount rate beta.

Sixth, our decomposition of the CAPM beta can also contribute to understanding the size premium, i.e. the higher average returns of small stocks relative to large stocks. The same pattern of cash-flow and discount-rate betas observable across book-to-market sorted portfolios can also be observed across size-sorted portfolios. Small stocks have a larger discount rate beta with respect to market discount rates, $\beta_{i,DD}$, than large stocks and a smaller (i.e. more negative) cash-flow beta with respect to market discount rates, $\beta_{i,CD}$, than large stocks – see last row of Panels E and G – confirming the finding of Campbell and Mei (1993) that cash flows of small stocks are more sensitive to changes in real interest rates. However, the spread in $\beta_{i,DD}$ between small stocks and large stocks is larger than the absolute value of their spread in $\beta_{i,CD}$. This finding suggests that the size premium is distinctively different from the value premium. Small stocks have higher "good" discount rate betas because their discount rates are more sensitive to changes in market discount rates. In contrast, growth stocks have higher "good" discount rate betas because their cash flows are less sensitive to changes in market discount rates. The higher "good" discount rate beta of small stocks may be due to the fact that small stocks are more dependend on bank credit than large stocks, which have better access to the equity market to finance their investment projects.

In order to check the robustness of our results to the choice of the sample period, we also report on the left-hand-side of each panel of Table 4 the beta decomposition over the full sample, December 1928 to December 2001. Campbell and Vuolteenaho (2004) document that value stocks have a higher exposure to market discount rate risk, $\beta_{i,C}$, than growth stocks in the pre-1963 period but a lower exposure in the post-1963 period. Our results contradict the finding of Campbell and Vuolteenaho (2004). Comparing the results across the two samples reveals that, although growth stocks have higher discount rate betas in the post-1963 sample than in the full sample, the spread between value and growth stocks does not change significantly.[10] Since the only difference between our methodology and Campbell and Vuolteenaho (2004) is that we compute betas using risk-adjusted excess returns (excess returns divided by their conditional volatility) and risk-adjusted innovations to economic state variables in the VAR, our results suggest that when controlling for volatility, the relative exposure between value and growth stocks to market discount rate news does not change over time.

4.4 Are Asset-Specific Cash-Flow and Discount-Rate Risks Priced?

We now proceed with cross-sectional asset pricing tests to evaluate the ability of our four-beta model to capture cross-sectional variation in average portfolio returns. The unconditional asset pricing model in (12) is tested against the traditional CAPM (where only the full market beta, $\beta_{i,m}$, matters), the two-beta I-CAPM model (both $\beta_{i,C}$ and $\beta_{i,D}$ matter) of Campbell and Vuolteenaho (2004) and the popular FF three factor model.

More specifically, we consider the following cross-sectional regression for the four-beta model:

$$E_T\left[R_i^e\right] = \lambda_0 + \lambda_{CC}\hat{\beta}_{i,CC} + \lambda_{CD}\hat{\beta}_{i,CD} + \lambda_{DC}\hat{\beta}_{i,DC} + \lambda_{DD}\hat{\beta}_{i,DD} + e_i, \tag{19}$$

and we test the above specification against the single-beta, CAPM:

$$E_T\left[R_i^e\right] = \lambda_0 + \lambda_m\hat{\beta}_{i,m} + e_i, \tag{20}$$

[10] We ran a series of Chow tests for structural breaks in the betas after December 1963 (available on request). These tests confirm that both cash-flow and discount rate betas are stable over time when time-variation in conditional volatility is taken into account in the construction of cash flow and discount rate news. In contrast, betas are structurally unstable when changes in conditional volatility are not accounted for as in Campbell and Vuolteenaho (2004).

the two-beta I-CAPM:

$$E_T\left[R_i^e\right] = \lambda_0 + \lambda_C \hat{\beta}_{i,C} + \lambda_D \hat{\beta}_{i,D} + e_i, \tag{21}$$

and the FF three-factor model:

$$E_T\left[R_i^e\right] = \lambda_0 + \lambda_m \hat{\beta}_{i,m} + \lambda_{SMB} \hat{\beta}_{i,SMB} + \lambda_{HML} \hat{\beta}_{i,HML} + e_i, \tag{22}$$

that adds the returns on size and book-to-market portfolios (namely, Small-Minus-Big (SMB) and High-Minus-Low(HML)) as competing factors to the standard CAPM market return.[11]

In all models (19) to (22), $E_T\left[R_i^e\right]$ denotes the full-sample estimate of the mean risk premium defined as the sample mean (simple) return on each portfolio in excess of the (simple) risk-free interest rate. We estimate the unconditional unrestricted prices of beta risks for all models ("factor models") as well as for the following restricted I-CAPM version of the four-beta model in (19):

$$E_T\left[R_i^e\right] = \lambda_0 + \gamma\lambda \hat{\beta}_{i,CC} + \lambda \hat{\beta}_{i,CD} + \gamma\lambda \hat{\beta}_{i,DC} + \lambda \hat{\beta}_{i,DD} + e_i \tag{23}$$

This last version enables us to estimate the coefficient of relative risk aversion γ and test the restrictions imposed by the model ($\lambda_{CC} = \lambda_{DC}$ and $\lambda_{CD} = \lambda_{DD}$).

[INSERT TABLE 5 HERE]

Panels A to D of Table 5 report the empirical findings. For each asset pricing cross-sectional regression, the table reports the estimated average pricing error (λ_0), the estimated beta prices of risk (λs) along with the standard errors (in parentheses), as well as the adjusted R^2 of the regression. Also, we conduct an F-test that all coefficients except the constant λ_0 are jointly equal to zero and we report the p-value of the test. For the two-factor and four-factor models we estimate both an unrestricted and a restricted version. Unrestricted

[11] The SMB and HML betas in (22) were calculated as the ratio of the covariance of contemporeneous asset returns with the SMB and HML portfolios returns. Since, to our knowledge, there are no theoretical reasons to expect a delay in the response of stock prices to these book-to-market and size factors, we employ the standard methodology and not that described in (18). However, the results are quantitavely the same when lags in the covariance terms of these betas are included.

estimates of the risk prices are obtained from a cross-sectional regression of average excess returns on a constant and the two and four betas respectively. The results are illustrated in the second and fourth column of each table. Given that the asset pricing restriction implies that the average pricing error in all models (19) to (23) must be equal to zero (under the null hypothesis that the model is correctly specified and the sources of risk (i.e. betas) provide a full description of the cross-sectional variation in average returns), we conduct a Wald test that λ_0 and the less statistically significant premium are jointly zero. If the test rejects the null hypothesis, we re-estimate the regression ignoring the constant given that the price of beta risk under consideration gets a lower p-value. Estimation results of the restricted models appear in the third and fifth column in all tables. Finally, for the four-beta model in (23), we report a Wald χ^2 statistic that tests for equality between the two pairs of risk premia related to market cash-flow and discount-rate risk ($\lambda_{CC} = \lambda_{DC}$ and $\lambda_{CD} = \lambda_{DD}$) as well as the estimated value (along with the p-value) of the coefficient of relative risk aversion, γ, and the price of "good" market risk λ. Asterisks $(^{***}), (^{**})$ and $(^{*})$ reported on the estimated risk premia (λs) indicate 1%, 5% and 10% statistical significance, respectively.

Our betas in (18) are estimated with errors. As a result, cross-sectional standard errors based on OLS are likely understated and p-values of F-tests and χ^2 tests are likely overstated since betas are assumed to be fixed in the cross-sectional regressions. In order to account for the uncertainty of the estimated betas, we conduct a set of Monte Carlo simulations as follows. First, we draw the betas from a normal distribution with mean and standard error equal to their sample estimates (see Table 4). Second, for each draw we run the asset pricing cross-sectional regressions and store the standard errors of the beta risk price estimates (λs and γ) and the p-values of the associated χ^2 tests of risk-premia equality ($\lambda_{CC} = \lambda_{DC}$ and $\lambda_{CD} = \lambda_{DD}$). We repeat this procedure 3.000 times and finally we report the average standard error of the estimated λs and γ, and average p-values of the χ^2 tests in squared brackets, respectively.[12]

Figure 1 plots the realized average excess returns versus the fitted excess returns of the four models in (19)-(22). If a model does a good job in explaining the cross-section of asset

[12] In an extensive Monte Carlo study Shanken and Zhou (2005) compare the performance of alternative estimators in a one-factor and three-factor model. They find that although OLS is less precise, inference based on it is fairly reliable in their senarios.

returns, then fitted and observed excess returns should line up along the 45 degree line. As such, these plots provide a visual representation of the ability of each model to match the realized cross-sectional spread in average excess returns.

[INSERT FIGURE 1 HERE]

Panel A of Table 5 reports the empirical findings for the 25 size-BE/ME double sorted common stock portfolios. Confirming the findings of Fama and French (1992), the traditional static CAPM performs poorly in explaining the cross-sectional variation in average returns, resulting in a low adj.-R^2 equal to 3.4% and a highly significant average pricing error equal to 0.029 ($s.e = 0.017$) per month. We then ask whether the two-beta and four beta models with unrestricted prices of beta risks can improve the empirical validity of the standard static CAPM and it is clear that they both do.

The two-factor model of Campbell and Vuolteenaho (2004) performs quite well and generates insignificant pricing errors ($\widehat{\lambda}_0 = -0.003, s.e = 0.015$) and statistically significant premia with the premium associated with market cash flow risk being considerably higher than the premium associated with market's discount rate risk ($\widehat{\lambda}_C = 0.077$ and $\widehat{\lambda}_D = 0.013$ with $s.e = 0.014$ and 0.001 respectively). A high adj.-R^2 of 42.4% shows that much of the cross-sectional variation in average returns is explained.

The four-factor I-CAPM model performs even better. Similar to the two-factor model of Campbell and Vuolteenaho (2004), the pricing error is small and statistically insignificant ($\widehat{\lambda}_0 = -0.002, s.e = 0.013$) but the adj.-$R^2$ increases from 40% to 53%. When the insignificant constant λ_0 is removed, the model in its restricted version yields a highly statistically significant and economically reasonable estimate for the relative risk aversion coefficient of 5.755 ($s.e = 0.739$), and a higher adj.-R^2 of 55%. Also, the model yields the predicted difference between the level of risk prices for the components of market cash-flow and discount-rate risk: the premia associated with market cash-flows (λ_{CC} and λ_{DC}) are 5 to 6 times higher than those associated with market discount rates (λ_{CD} and λ_{DD}). Evidence based on simulations supports the theoretical restriction of equality between the two pairs of risk premia related to market cash-flow and discount-rate risk, respectively. The average p-values are 0.075 and 0.139 indicating that we cannot safely reject the null that $\lambda_{CC} = \lambda_{DC}$ and $\lambda_{CD} = \lambda_{DD}$.

The last column of Panel A reports estimation results of the FF three-factor model. As expected, the FF model produces the best fit among the four models with an adj.-R^2 of 80%.[13] However, it generates large and statistically significant pricing errors ($\widehat{\lambda}_0 = 0.019, s.e. = 0.003$) and, moreover, delivers a negative risk premium for the total market risk factor ($\widehat{\lambda}_m = -0.017, s.e. = 0.003$). Overall, both the two-factor and the four-factor I-CAPM model perform better than the FF model in terms of pricing errors. Among the two I-CAPM specifications, the four-beta model performs better than the two-beta model both in terms of mean pricing error and adjusted R^2.

Panel B of Table 5 reports our model estimates for three sets of 10 single-sorted portfolios according to book-to-market, dividend-price ratio and market value. Our four-beta model again improves the ability of the disappointing static CAPM and the well performing two-beta I-CAPM to capture the spread in mean asset premia. The proportion of the explained cross-sectional variability increases from 46.4% (two-beta model) to an impressive 83.1%, while the average pricing error is still highly insignificant. Most importantly, and even when the insignificant constant is included in the regression, all the slope coefficients (except λ_{CD}) are significant, indicating that the approach of decomposing cash flow and discount rate market risks yields interesting insights for the determination of average risk premia. Once the constant λ_0 is removed, however, all four risk prices are highly significant. Further, the factor of proportionality that is restricted to be equal to the coefficient of relative risk aversion is both economically and statistically significant ($\widehat{\gamma} = 5.304$, $s.e. = 0.551$). For this group of portfolios, although we cannot reject the equality hypothesis for the market discount-rate premia λ_{CD} and λ_{DD}, we can safely reject it for the cash-flow premia. Again, the FF model produces a better fit (adj.-$R^2 = 93\%$) but high and significant pricing errors ($\widehat{\lambda}_0 = 0.005, s.e = 0.002$ and 0.003 for simulated data).

We also test the empirical validity of our four-factor model using the 25 book-to-market portfolios as well as 20 risk portfolios sorted on market betas and betas associated with innovations to the state variables.[14] The approach of sorting stocks according to past risk

[13] This is no surprise because mimicking portfolio models such as the FF model are more likely to beat structural asset pricing models in terms of cross-sectional R^2 due to the fact that they explain asset returns on the mean-variance frontier as linear combinations of a set of "mimicking" portfolio returns which also lie on the mean-variance frontier.

[14] For recent studies that relate loadings of unexpected returns on innovations of macroeconomic state

rather than firm-specific characteristics can gauge the impact of data snooping on empirical findings that reveal relationships between characteristics-sorted portfolio trading strategies and average returns. Panel C of Table 5 shows that the static CAPM still performs badly and generates a very low adj.-R^2 of -0.9%, statistically significant average pricing errors ($\widehat{\lambda}_0 = 0.014$, $s.e. = 0.009$) and a negative but insignificant estimate for the market premium ($\widehat{\lambda}_m = -0.007, s.e. = 0.009$). Thus, market beta, as a single aggregate risk measure, fails to capture the cross-sectional spread in returns. Compared to the two-beta model, the four-beta model increases the percentage of explained cross-sectional return variability from 44% to 60%. Confirming our previous results, the model produces small and insignificant pricing errors and reasonable estimates of risk aversion ($\hat{\gamma} = 5.788, s.e. = 0.519$). Moreover, the observed pattern in cash-flow and discount-rate prices of risk is in line with our previous tests: still, risk prices associated with the two components of market cash-flow risk ($\widehat{\lambda}_{CC} = 0.062, \widehat{\lambda}_{DC} = 0.072$) are much higher than the risk prices associated with market discount-rate risk ($\widehat{\lambda}_{CD} = 0.008, \widehat{\lambda}_{DD} = 0.013$). The equality hypothesis of risk premia implied by the asset pricing model in (19) cannot be rejected from the simulation results (average p-values 0.055 and 0.097 respectively). Finally, the three-factor FF model performs no better than before. Once again, the model can not eliminate the average pricing error ($\widehat{\lambda}_0 = 0.007, s.e. = 0.001$) and cannot yield a positive relationship between average excess returns and total market risk ($\widehat{\lambda}_m = -0.003, s.e. = 0.001$).

Finally, for experimental reasons, we include all the 5 sets of portfolios (25 size/book-to-market, 20 risk, 10 book-to-market, 10 dividend-price and 10 size sorted) in one cross-sectional regression. Panel D in Table 5 reports the results. Similar to the previous empirical findings, the market overall beta, β_{im}, explains none of the cross-sectional variation in average returns. Both the two-beta and the four-beta models again produce insignificant pricing errors and risk prices in line with economic theory. However, our four-beta specification in (23) increases the ability of the two-beta model by more than 20% in terms of explanatory power. The point estimate of the CRRA is significant, economically acceptable and similar to the one generated from the previous samples ($\widehat{\gamma} = 5.594, s.e. = 0.383$). The equality hypothesis of risk premia cannot be rejected with the average p-values of the χ^2 tests being

variables and the global size and book-to-market mimicking portfolio returns of the Fama-French (1993) three factor model, see Petkova (2005) and Aretz, Bartram and Pope (2005), and the references therein.

0.034 and 0.061, respectively. Finally, the same quantitative arguments against the FF model apply here.

Overall, using a wide set of portfolios, we find that the four-beta model clearly improves the two-beta model of Campbell and Vuolteenaho (2004) in terms of statistical fit and performs far better than the three-factor Fama and French (1993) model in terms of average pricing error. Moreover, our estimates suggest that long-run cash-flow and discount-rate risk is priced according to Merton's I-CAPM with an economically reasonable CRRA coefficient.

5 Conclusions

This paper builds on the decomposition of the overall market risk into parts reflecting time variation related to the dynamics of portfolio-specific and aggregate market cash flows and discount rates. Following the current literature on the identification of long-run risks and extending the methodology of Campbell and Vuolteenaho (2004) and Campbell, Polk and Vuolteenaho (2005) to account for time-varying conditional volatility in excess returns and economic state variables, we decompose market betas into four sub-betas, two associated with market cash-flows and two with market discount-rates. Using a VAR to generate innovations to cash-flows and future returns and a discrete time version of Merton's I-CAPM, we ask whether the components of overall risk related to changes in expectations about future dividends and future returns are rationally priced.

Our study extends Campbell and Vuolteenaho (2004) and Campbell, Polk and Vuolteenaho (2005) in several respects: First, by relaxing the assumption of homoskedasticity of excess returns and economic state variables, we are able to compute risk-adjusted news about future cash flows and discount rates by controlling with the conditional volatility of returns and state variables which predict variations of future returns. This is equivalent to assuming that investors put a lower weight to information originating from more volatile state variables when updating their forecasts about future returns and cash flows. We find that accounting for volatility can control for structural breaks in the exposure of value and growth stocks to market cash-flow and discount-rate risks, contradicting evidence presented in Campbell and Vuolteenaho (2004) that the spread in the discount rate "bad" beta between value and growth stocks changes significantly after 1963.

Second, while Campbell, Polk and Vuolteenaho (2005) estimate asset-specific discount-rate news from a VAR where the state variables are portfolio-related attributes, we follow the advise of rational asset pricing theory and use a common set of economy-wide state variables to forecast expected returns for all stocks including the market portfolio. Following Merton (1973), the innovations in these variables are then used as economy-wide risk factors in the cross-sectional asset pricing tests. It turns out that allowing for a common set of risk factors across all stocks along with time-variation in conditional volatility increases considerably the spread in long-run cash-flow and discount-rate betas between value and growth stocks, compared to the estimates of Campbell, Polk and Vuolteenaho (2005). Thus, our method of estimating long-run cash-flow and discount-rate risks gives a better description of the cross-section of excess returns.

Third, we apply the four-beta model to size-sorted portfolios and ask whether it can account for the observed higher average return of small stocks relative to large stocks, i.e. the size-premium. We find that the same pattern of cash-flow and discount-rate betas observable across book-to-market sorted portfolios can also be observed across size-sorted portfolios. However, the size premium is distinctively different from the value premium, requiring a different economic explanation. In particular, our findings suggest that small stocks have a higher "good" discount rate beta because their discount rates are more sensitive to changes in market discount rates, in contrast to growth stocks, which have higher "good" discount rate betas because their cash flows are less sensitive to changes in market discount rates. We hypothesize that the higher "good" discount rate beta of small stocks is due to the fact that small stocks rely more heavily on bank credit, in contrast to large stocks, which have better access to the equity market as a source of financing.

Fourth, we test whether the four components of the overall market beta are priced in the cross-section of stock returns according to a discrete time version of Merton's (1973) I-CAPM that identifies changes in expectations about future dividend growth and future risk premia as long-run risk factors. During the period December 1928 to December 2001, the four-beta model performs well in pricing average excess returns on single- and double-sorted portfolios according to market capitalization, book-to-market, dividend-price ratios and past risk. The model produces insignificant pricing errors, high estimates for the explained cross-sectional variation (which in some cases exceeds 80%) in average monthly returns and both economically and statistically acceptable estimates for the coefficient of relative risk aversion. Overall, the four-beta model clearly improves the two-beta model of Campbell and Vuolteenaho (2004) in terms of statistical fit and performs better than the three-factor Fama and French (1993) model in terms of average pricing error.

We find that the risks associated with permanent shocks to market returns, as these are described by the two market cash-flow betas, earn higher unconditional risk prices compared to the risk prices associated with market discount-rate risks. However, all four components of the total market systematic risk are required in order to improve the ability of the static CAPM to capture the cross-sectional variation of mean premia on common stock portfolios.

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Table 1. VAR estimates for market portfolio

	$r_{m,t+1}$	TY_{t+1}	$p_{t+1} - e_{t+1}$	VS_{t+1}
constant	0.062 (0.020)	0.046 (0.097)	0.019 (0.013)	0.014 (0.017)
$r_{m,t}$	0.093 (0.034)	0.033 (0.165)	0.519 (0.022)	−0.008 (0.029)
TY_t	0.006 (0.003)	0.880 (0.016)	0.002 (0.002)	0.002 (0.003)
$p_t - e_t$	−0.015 (0.005)	−0.036 (0.026)	0.994 (0.004)	0.000 (0.005)
VS_t	−0.012 (0.006)	0.082 (0.028)	−0.003 (0.004)	0.991 (0.005)
R^2	2.6%	82.4%	99.1%	98.4%
F-stat.	5.713	1020.446	22898.7	13400.13
LM Test for Heteroscedasticity (ARCH Test: lag = 4)				
	$\hat{u}_{r_m}$	$\hat{u}_{TY}$	$\hat{u}_{p-e}$	$\hat{u}_{VS}$
F-stat.	25.071	24.652	13.264	22.841
p-value	[0.000]	[0.000]	[0.000]	[0.000]

Table 2: Estimates of univariate GARCH(1,1) models of market portfolio VAR innovations

Parameter	$h_{r_m,t}$	$h_{TY,t}$	$h_{p-e,t}$	$h_{VS,t}$
k_j	$5.75e-05$	$9.39e-05$	$3.08e-05$	0.000
	$(1.98e-05)$	$(4.11e-05)$	$(9.76e-06)$	$(1.76e-05)$
μ_j^2	0.107	0.135	0.082	0.048
	(0.017)	(0.019)	(0.017)	(0.007)
δ_j^2	0.877	0.805	0.892	0.905
	(0.017)	(0.014)	(0.022)	(0.014)
	LM Test for Heteroscedasticity (ARCH Test: lag = 4)			
	$\hat{z}_{r_m}$	$\hat{z}_{TY}$	$\hat{z}_{p-e}$	$\hat{z}_{VS}$
F-stat.	0.331	0.890	0.586	0.223
p-value	[0.857]	[0.469]	[0.673]	[0.926]

Table 3: Market portfolio cash-flow and discount-rate news

	Covariance matrix of news			News corr/st.d.	
	N_m^C	N_m^D		N_m^C	N_m^D
N_m^C	0.385	0.486	N_m^C	0.621	0.621
N_m^D	0.486	1.590	N_m^D	0.621	1.262
	Correlations of innovations with news			Functions	
Innovations/News	N_m^C	N_m^D		N_m^C	N_m^D
$r_m - r_f$	-0.162	-0.874	$r_m - r_f$ shock	0.599	-0.401
TY	0.039	0.011	TY shock	0.010	0.010
$p - e$	-0.692	-0.953	$p - e$ shock	-0.889	-0.889
VS	-0.377	-0.221	VS shock	-0.263	-0.263

Table 4. Cash-flow and discount-rate betas for 25 book-to-market/size portfolios

Panel A. Total Market Betas, $\beta_{i,m}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	0.920	0.944	0.948	0.917	0.913	-0.007	small	0.983	0.949	0.944	0.906	0.912	-0.071
	(0.053)	(0.049)	(0.047)	(0.045)	(0.045)			(0.067)	(0.071)	(0.071)	(0.073)	(0.070)	
2	0.956	0.945	0.909	0.892	0.906	-0.050	2	0.940	0.911	0.889	0.849	0.853	-0.087
	(0.041)	(0.041)	(0.042)	(0.044)	(0.043)			(0.067)	(0.069)	(0.067)	(0.066)	(0.068)	
3	0.908	0.951	0.917	0.909	0.871	-0.037	3	0.896	0.939	0.853	0.828	0.802	-0.093
	(0.039)	(0.040)	(0.041)	(0.040)	(0.045)			(0.064)	(0.066)	(0.062)	(0.061)	(0.068)	
4	0.929	0.919	0.932	0.916	0.913	-0.015	4	0.921	0.903	0.874	0.819	0.813	-0.108
	(0.038)	(0.039)	(0.040)	(0.040)	(0.045)			(0.062)	(0.066)	(0.063)	(0.057)	(0.064)	
large	0.925	0.948	0.871	0.859	0.863	-0.062	large	0.897	0.891	0.784	0.759	0.749	-0.148
	(0.037)	(0.036)	(0.042)	(0.041)	(0.047)			(0.057)	(0.056)	(0.062)	(0.056)	(0.059)	
diff.	-0.005	-0.004	0.077	0.058	0.050		diff.	0.087	0.058	0.161	0.146	0.163	

Panel B. Cash-Flow Betas, $\beta_{i,C}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	-0.065	-0.071	-0.051	-0.051	-0.039	0.025	small	-0.128	-0.122	-0.106	-0.105	-0.093	0.034
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)			(0.042)	(0.039)	(0.039)	(0.040)	(0.038)	
2	-0.096	-0.077	-0.060	-0.044	-0.037	0.059	2	-0.164	-0.128	-0.117	-0.097	-0.095	0.069
	(0.033)	(0.031)	(0.032)	(0.032)	(0.032)			(0.041)	(0.040)	(0.041)	(0.039)	(0.037)	
3	-0.103	-0.072	-0.045	-0.036	-0.024	0.078	3	-0.155	-0.122	-0.099	-0.080	-0.072	0.083
	(0.030)	(0.032)	(0.032)	(0.032)	(0.033)			(0.039)	(0.044)	(0.041)	(0.038)	(0.040)	
4	-0.100	-0.066	-0.038	-0.028	-0.023	0.076	4	-0.164	-0.113	-0.077	-0.071	-0.070	0.094
	(0.032)	(0.032)	(0.032)	(0.031)	(0.032)			(0.042)	(0.044)	(0.042)	(0.037)	(0.032)	
large	-0.112	-0.083	-0.044	-0.020	-0.022	0.090	large	-0.178	-0.120	-0.083	-0.049	-0.048	0.130
	(0.029)	(0.031)	(0.033)	(0.031)	(0.029)			(0.033)	(0.042)	(0.040)	(0.035)	(0.032)	
diff.	0.047	0.012	-0.008	-0.032	-0.018		diff.	0.051	-0.002	-0.023	-0.056	-0.045	

Panel C. Discount-Rate Betas, $\beta_{i,D}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	0.985	1.015	0.999	0.968	0.953	-0.032	small	1.113	1.073	1.052	1.012	1.007	-0.107
	(0.068)	(0.062)	(0.064)	(0.061)	(0.061)			(0.079)	(0.084)	(0.083)	(0.087)	(0.082)	
2	1.052	1.023	0.970	0.936	0.943	-0.109	2	1.109	1.042	1.008	0.948	0.950	-0.159
	(0.053)	(0.054)	(0.059)	(0.060)	(0.060)			(0.076)	(0.080)	(0.082)	(0.080)	(0.085)	
3	1.010	1.023	0.962	0.944	0.895	-0.116	3	1.054	1.064	0.954	0.909	0.874	-0.180
	(0.051)	(0.053)	(0.058)	(0.054)	(0.061)			(0.073)	(0.075)	(0.075)	(0.077)	(0.085)	
4	1.028	0.985	0.970	0.944	0.937	-0.091	4	1.089	1.018	0.952	0.890	0.884	-0.205
	(0.049)	(0.052)	(0.056)	(0.055)	(0.061)			(0.068)	(0.079)	(0.078)	(0.073)	(0.079)	
large	1.037	1.031	0.915	0.879	0.885	-0.152	large	1.080	1.014	0.868	0.808	0.797	-0.283
	(0.049)	(0.046)	(0.054)	(0.059)	(0.061)			(0.067)	(0.064)	(0.074)	(0.072)	(0.075)	
diff.	-0.053	-0.015	0.085	0.089	0.068		diff.	0.034	0.060	0.185	0.205	0.210	

Panel D. Cash-Flow Cash-Flow Betas, $\beta_{i,CC}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	0.753	0.732	0.475	0.409	0.641	-0.112	small	0.765	0.747	0.474	0.408	0.641	-0.124
	(0.043)	(0.039)	(0.040)	(0.038)	(0.042)			(0.050)	(0.047)	(0.046)	(0.046)	(0.050)	
2	0.408	0.335	0.397	0.497	0.690	0.282	2	0.389	0.333	0.401	0.506	0.698	0.309
	(0.037)	(0.037)	(0.033)	(0.036)	(0.037)			(0.041)	(0.041)	(0.035)	(0.039)	(0.051)	
3	0.370	0.349	0.334	0.453	0.583	0.213	3	0.358	0.356	0.329	0.463	0.571	0.213
	(0.044)	(0.029)	(0.026)	(0.026)	(0.030)			(0.044)	(0.030)	(0.030)	(0.029)	(0.041)	
4	0.234	0.316	0.423	0.395	0.695	0.461	4	0.207	0.313	0.432	0.395	0.698	0.491
	(0.023)	(0.026)	(0.022)	(0.022)	(0.036)			(0.028)	(0.027)	(0.025)	(0.027)	(0.054)	
large	0.139	0.243	0.369	0.419	0.471	0.332	large	0.092	0.237	0.360	0.420	0.467	0.375
	(0.014)	(0.014)	(0.020)	(0.023)	(0.038)			(0.019)	(0.020)	(0.026)	(0.030)	(0.051)	
diff.	0.614	0.489	0.107	-0.010	0.170		diff.	0.674	0.511	0.114	-0.012	0.174	

Panel E. Cash-Flow Discount-Rate Betas, $\beta_{i,CD}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	-1.712	-1.397	-1.272	-1.106	-1.640	0.072	small	-1.856	-1.685	-1.172	-0.960	-1.635	0.221
	(0.089)	(0.100)	(0.080)	(0.081)	(0.080)			(0.119)	(0.124)	(0.104)	(0.105)	(0.108)	
2	-1.139	-0.935	-1.001	-1.257	-1.549	-0.409	2	-0.885	-0.710	-0.856	-1.235	-1.738	-0.853
	(0.083)	(0.079)	(0.071)	(0.071)	(0.082)			(0.113)	(0.103)	(0.096)	(0.095)	(0.119)	
3	-1.204	-0.787	-0.670	-0.932	-1.218	-0.014	3	-0.863	-0.659	-0.606	-1.009	-1.383	-0.520
	(0.090)	(0.061)	(0.063)	(0.059)	(0.079)			(0.118)	(0.082)	(0.081)	(0.084)	(0.111)	
4	-0.474	-0.694	-0.818	-0.773	-1.437	-0.963	4	-0.272	-0.559	-0.876	-0.857	-1.787	-1.515
	(0.058)	(0.060)	(0.059)	(0.056)	(0.093)			(0.080)	(0.081)	(0.085)	(0.071)	(0.117)	
large	-0.069	-0.201	-0.401	-0.684	-1.346	-1.277	large	-0.010	-0.281	-0.620	-0.925	-1.452	-1.442
	(0.036)	(0.041)	(0.067)	(0.070)	(0.071)			(0.049)	(0.061)	(0.086)	(0.084)	(0.086)	
diff.	-1.642	-1.195	-0.871	-0.422	-0.293		diff.	-1.846	-1.404	-0.552	-0.035	-0.182	

Panel F. Discount-Rate Cash-Flow Betas, $\beta_{i,DC}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	-0.818	-0.803	-0.527	-0.460	-0.680	0.138	small	-0.893	-0.869	-0.581	-0.513	-0.735	0.158
	(0.063)	(0.058)	(0.059)	(0.057)	(0.064)			(0.078)	(0.073)	(0.066)	(0.062)	(0.075)	
2	-0.504	-0.412	-0.458	-0.541	-0.727	-0.223	2	-0.553	-0.462	-0.517	-0.603	-0.793	-0.239
	(0.058)	(0.057)	(0.053)	(0.057)	(0.058)			(0.062)	(0.058)	(0.056)	(0.062)	(0.072)	
3	-0.472	-0.421	-0.379	-0.489	-0.607	-0.134	3	-0.513	-0.478	-0.428	-0.543	-0.643	-0.130
	(0.065)	(0.049)	(0.045)	(0.047)	(0.048)			(0.065)	(0.051)	(0.047)	(0.051)	(0.060)	
4	-0.334	-0.382	-0.461	-0.423	-0.718	-0.384	4	-0.371	-0.426	-0.509	-0.466	-0.768	-0.397
	(0.043)	(0.047)	(0.045)	(0.042)	(0.053)			(0.044)	(0.050)	(0.050)	(0.047)	(0.068)	
large	-0.251	-0.325	-0.412	-0.438	-0.493	-0.242	large	-0.270	-0.357	-0.443	-0.469	-0.515	-0.245
	(0.030)	(0.031)	(0.030)	(0.036)	(0.055)			(0.034)	(0.038)	(0.040)	(0.044)	(0.063)	
diff.	-0.567	-0.478	-0.114	-0.022	-0.188		diff.	-0.623	-0.513	-0.138	-0.044	-0.219	

Panel G. Discount-Rate Discount-Rate Betas, $\beta_{i,DD}$

	Sample: 1928-2001							Sample: 1963-2001					
	growth	2	3	4	value	diff		growth	2	3	4	value	diff
small	2.696	2.412	2.271	2.074	2.592	-0.104	small	2.969	2.759	2.224	1.973	2.642	-0.328
	(0.084)	(0.089)	(0.078)	(0.081)	(0.082)			(0.119)	(0.121)	(0.106)	(0.109)	(0.115)	
2	2.192	1.958	1.971	2.193	2.492	0.300	2	1.994	1.752	1.864	2.184	2.688	0.694
	(0.086)	(0.086)	(0.076)	(0.076)	(0.080)			(0.117)	(0.112)	(0.105)	(0.106)	(0.116)	
3	2.214	1.810	1.632	1.876	2.113	-0.101	3	1.917	1.723	1.560	1.918	2.258	0.340
	(0.102)	(0.068)	(0.064)	(0.061)	(0.068)			(0.135)	(0.093)	(0.087)	(0.087)	(0.099)	
4	1.502	1.679	1.788	1.717	2.374	0.871	4	1.361	1.577	1.828	1.747	2.671	1.311
	(0.066)	(0.068)	(0.061)	(0.055)	(0.081)			(0.089)	(0.095)	(0.091)	(0.076)	(0.108)	
large	1.106	1.232	1.315	1.563	2.231	1.125	large	1.090	1.295	1.488	1.732	2.249	1.159
	(0.043)	(0.045)	(0.050)	(0.051)	(0.070)			(0.060)	(0.067)	(0.071)	(0.067)	(0.092)	
diff.	1.590	1.180	0.956	0.511	0.361		diff.	1.880	1.464	0.736	0.240	0.392	

Table 5. Cross-sectional asset pricing tests

Panel A. 25 BE/ME portfolios

	CAPM	Two-factor I-CAPM		Four-factor I-CAPM		Fama-French
λ_0	0.029* (0.016) [0.015]	−0.003 (0.015) [0.015]		−0.002 (0.013) [0.012]		0.019*** (0.003) [0.004]
λ_m	−0.023 (0.017) [0.017]					−0.017*** (0.003) [0.004]
λ_C		0.083*** (0.031) [0.030]	0.077*** (0.014) [0.015]			
λ_D		0.017 (0.017) [0.017]	0.013*** (0.001) [0.001]			
λ_{CC}				0.076** (0.029) [0.027]	0.073*** (0.015) [0.015]	
λ_{CD}				0.011 (0.016) [0.014]	0.009*** (0.002) [0.002]	
λ_{DC}				0.087*** (0.029) [0.028]	0.084*** (0.016) [0.016]	
λ_{DD}				0.016 (0.015) [0.014]	0.014*** (0.002) [0.002]	
λ_{SMB}						0.004*** (0.001) [0.001]
λ_{HML}						0.006*** (0.001) [0.001]
adj.-R^2	3.4%	39.9%	42.4%	52.7%	54.9%	80.6%
F-test (all zero) (p-value)		8.983 (0.001)		7.688 (0.001)		29.096 (0.000)
χ^2- test (p-value)		$\lambda_0 = \lambda_D = 0$ 194.294 (0.000)		$\lambda_0 = \lambda_{CD} = 0$ 18.465 (0.000)	$\lambda_{CC} = \lambda_{DC}$ 5.447 (0.019) [0.075]	
χ^2- test (p-value)					$\lambda_{CD} = \lambda_{DD}$ 8.277 (0.004) [0.139]	
CRRA (γ) (s.e)					5.775*** (0.739) [1.019]	
λ (s.e)					0.013*** (0.001) [0.001]	

Panel B. 30 portfolios: 10 BE/ME, 10 D/P and 10 size portfolios

	CAPM	Two-factor I-CAPM		Four-factor I-CAPM		Fama-French
λ_0	0.010* (0.006) [0.006]	−0.004 (0.005) [0.005]		−0.002 (0.003) [0.003]		0.005*** (0.002) [0.003]
λ_m	−0.003 (0.006) [0.006]					$-1.95e-05$ (0.002) [0.004]
λ_C		0.071*** (0.015) [0.015]	0.0061*** (0.009) [0.010]			
λ_D		0.016** (0.006) [0.006]	0.012*** (0.001) [0.001]			
λ_{CC}				0.024* (0.012) [0.012]	0.019*** (0.009) [0.009]	
λ_{CD}				0.006 (0.004) [0.004]	0.004*** (0.001) [0.001]	
λ_{DC}				0.028* (0.014) [0.014]	0.023*** (0.011) [0.011]	
λ_{DD}				0.009** (0.004) [0.004]	0.008*** (0.001) [0.002]	
λ_{SMB}						0.002*** (0.001) [0.001]
λ_{HML}						0.003*** (0.000) [0.001]
adj.$-R^2$	−2.7%	45.6%	46.4%	82.7%	83.1%	93.1%
F-test (all zero) (p-value)		13.178 (0.000)		35.733 (0.000)		87.741 (0.000)
χ^2-test (p-value)		$\lambda_0 = \lambda_D = 0$ 321.302*** (0.000)		$\lambda_0 = \lambda_{CD} = 0$ 14.429*** (0.001)	$\lambda_{CC} = \lambda_{DC}$ 0.846 (0.357) [0.602]	
χ^2-test (p-value)					$\lambda_{CD} = \lambda_{DD}$ 17.017 (0.000) [0.002]	
CRRA (γ) (s.e.)					5.304 (0.551) [0.552]	
λ (s.e.)					0.012 (0.001) [0.001]	

Panel C. 45 portfolios: 25 BE/ME and 20 risk portfolios

	CAPM	Two-factor I-CAPM		Four-factor I-CAPM		Fama-French
λ_0	0.014	0.001		0.004		0.007***
	(0.009)	(0.007)		(0.006)		(0.001)
	[0.009]	[0.007]		[0.006]		[0.002]
λ_m	-0.007					-0.003**
	(0.009)					(0.001)
	[0.009]					[0.002]
λ_C		0.071***	0.073***			
		(0.015)	(0.010)			
		[0.015]	[0.012]			
λ_D		0.011	0.012***			
		(0.008)	(0.001)			
		[0.008]	[0.001]			
λ_{CC}				0.056***	0.062***	
				(0.014)	(0.010)	
				[0.014]	[0.010]	
λ_{CD}				0.004	0.008***	
				(0.007)	(0.001)	
				[0.007]	[0.001]	
λ_{DC}				0.065**	0.072***	
				(0.015)	(0.011)	
				[0.015]	[0.011]	
λ_{DD}				0.008	0.013***	
				(0.007)	(0.001)	
				[0.007]	[0.001]	
λ_{SMB}						0.002***
						(0.001)
						[0.001]
λ_{HML}						0.004***
						(0.001)
						[0.001]
adj.$-R^2$	-0.9%	42.7%	44.0%	60.4%	61.0%	68.1%
F-test (all zero)		17.411		17.790		29.291
(p-value)		(0.000)		(0.000)		(0.000)
		$\lambda_0 = \lambda_D = 0$		$\lambda_0 = \lambda_{CD} = 0$	$\lambda_{CC} = \lambda_{DC}$	
χ^2-test		315.247		38.683	7.699	
(p-value)		(0.000)		(0.000)	(0.005)	
					[0.055]	
					$\lambda_{CD} = \lambda_{DD}$	
χ^2-test					16.904	
(p-value)					(0.000)	
					[0.097]	
CRRA (γ)					5.788	
(s.e.)					[0.519]	
					[0.728]	
λ					0.012	
(s.e.)					(0.001)	
					[0.001]	

Panel D. 75 portfolios: 25 size/BE/ME, 20 risk, 10 BE/ME, 10 D/P and 10 size portfolios

	CAPM	Two-factor I-CAPM		Four-factor I-CAPM		Fama-French
λ_0	0.012** (0.005) [0.005]	-0.002 (0.004) [0.004]		-0.001 (0.003) [-0.003]		0.007*** (0.001) [0.002]
λ_m	-0.004 (0.005) [-0.809]					-0.002^{**} (0.001) [0.002]
λ_C		0.073*** (0.011) [0.011]	0.068*** (0.007) [0.007]			
λ_D		0.015*** (0.005) [0.005]	0.012*** (0.000) [0.001]			
λ_{CC}				0.052*** (0.009) [5.262]	0.049*** (0.007) [6.824]	
λ_{CD}				0.009** (0.004) [2.272]	0.007*** (0.001) [7.812]	
λ_{DC}				0.060*** (0.010) [5.601]	0.058*** (0.008) [6.943]	
λ_{DD}				0.013*** (0.004) [3.294]	0.011*** (0.001) [11.383]	
λ_{SMB}						0.001*** (0.000) [0.001]
λ_{HML}						0.004** (0.001) [0.002]
adj.$-R^2$	-0.4%	44.4%	44.9%	64.8%	65.3%	73.3%
F-test (all zero) (p-value)		30.543 (0.000)		35.193 (0.000)		64.803 (0.000)
χ^2-test (p-value)		$\lambda_0 = \lambda_D = 0$ 618.399 (0.000)		$\lambda_0 = \lambda_{CD} = 0$ 60.483 (0.000)	$\lambda_{CC} = \lambda_{DC}$ 9.889 (0.002) [0.034]	
χ^2-test (p-value)					$\lambda_{CD} = \lambda_{DD}$ 29.874 (0.000) [0.061]	
CRRA (γ) (s.e.)					5.594 (0.383) [0.604]	
λ (s.e.)					0.012 (0.000) [0.001]	

Figure 1. Realized vs Fitted Average Excess Returns on 25 Book-to-Market Portfolios