Beta under the microscope or why the CAPM failed

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Abstract

We break the beta of a stock with the market portfolio into eight components related to future market-wide and firm-specific cash flows and discount rates in up and down markets. This decomposition naturally accounts for investors' loss aversion in the framework of the intertemporal CAPM approximation. Systematic risks embodied in stocks' cash-flow sensitivities to permanent aggregate shocks during market declines command a positive and highly significant premium. Moreover, the empirical fit of the standard CAPM substantially improves when risks are measured accurately. Our findings highlight the importance of downside fluctuations in the slow-moving component of fundamentals for asset pricing.

JEL classification: G11, G12

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I. Introduction

The concept of market beta–asset's tendency to comove with the market–is central to asset pricing. The static CAPM (capital asset pricing model) implies that differences in exposure to market risk should rationalize differences in expected returns across assets (Sharpe (1964) and Lintner (1965)). Empirically, however, the standard market beta reveals virtually no power to explain patterns in returns on stocks of different types of firms (Fama and French (1992)). If stocks are priced by discounting their cash flows, then both news about cash flows and discount rates should affect the measures of systematic risk that rational investors use to evaluate price movements. Moreover, if long-term investors care more about hedging against permanent rather than temporary shocks–as in the Merton's (1973) intertemporal CAPM–asset's cash-flow beta should obtain a higher compensation than asset's discount-rate beta. Recently, Campbell et al. (2010) argue that cash flows and discount rates at both market- and firm-level are important as systematic risk measures on equity investments.

This paper breaks the beta of a stock with the market portfolio into eight components related to future market-wide and firm-level cash flows and discount rates in up and down markets. This decomposition arises as a natural extension of a log-linearized approximation of the intertemporal CAPM which takes into account aversion related to downside movements in market-wide and firm-level news. More specifically, we distinguish between sensitivities of stocks' cash-flow and discount-rate components to permanent and transitory aggregate news in periods of above-average (upside) and below-average (downside) market performance. Ang et al. (2006), among others, show that a cross-section of stock returns reflects a premium for bearing downside risk. Our findings highlight the importance of downside fluctuations in the slow-moving persistent component of fundamentals in understanding the risk exposure of assets. This evidence provides further support to long-run risks models in Bansal and Yaron (2004), Bansal et al. (2009), and Da (2009) which emphasize the role of low-frequency movements in consumption and dividends, in accounting for several puzzles on asset markets. After substituting out consumption from a standard intertemporal asset pricing model–as in the framework of Campbell (1993)–permanent downside risks dominate while transitory fluctuations cancel out.

Putting the market beta under the microscope reveals that systematic risks embodied in stocks' cash-flow sensitivities to permanent aggregate shocks during market declines command a positive and highly significant premium. The cash flows of stocks with high book-to-market ratios, low market equity and strong past performance, i.e. value, small and winner stocks, hide an exposure to aggregate cash-flow shocks in hard times of bear markets. In contrary, stocks with low book-to-market ratios, high market equity and weak past performance, i.e. growth, large and loser stocks, are sensitive to aggregate discount-rate shocks in hard times of bear markets. Echoing Campbell et al. (2010), we find that growth stocks are not merely "glamour stocks" whose systematic risks are purely driven by investor sentiment. More generally, systematic risks embodied in stocks' betas are primarily driven by the downside risk exposure of their fundamentals. Disappointment aversion of agents who place a greater weight on losses as opposed to gains is a key to reach this conclusion.

Understanding the relative importance of cash-flow and discount-rate news–the two fundamental determinants of asset values–is a crucial issue in modern finance. For instance, Campbell and Vuolteenaho (2004) decompose the market beta into a "bad beta" component attributed to news about the market's future cash flows–which is tightly linked to production–and a "good beta" component attributed to news about the market's discount rates–which reflects time-varying risk aversion or investor sentiment. The authors show that differences in "bad betas" help explain value and size premia in stock returns. Galsband and Nitschka (2013) employ the setup of Campbell and Vuolteenaho (2004) to recognize a common source of systematic risk in stock and foreign currency returns behind the market's cash flows. Campbell et al. (2010) and Koubouros et al. (2010) highlight significant links between firm-wide and market-wide persistent returns' components, while Botshekan et al. (2013) and Galsband (2012) demonstrate that a cross-section of US and international stocks reflects their downside risk exposure to market cash flows.

In this paper, we propose a natural extension of the beta decomposition approach which conveniently encompasses long-lived permanent and short-lived temporary shocks to individual stocks' and total market returns and the asymmetry in agents preferences with respect to gains versus losses. Our beta representation is comprehensive and easily tractable and leads to economically intuitive implications. Taking a closer look at proximate symptoms of stock market fluctuations reveals important insights about stock fundamentals which remain unexplored in the literature so far. Empirically, our eight-beta model performs far better than the previously proposed two- and four-beta models and the benchmark three-factor model of Fama and French (1993) in terms of overall fit, precision of estimates and magnitude of pricing errors. Our analysis emphasizes downside risks in slow-moving component of fundamentals as the central determinant behind the risk-return trade-off on equity markets.

The organization of the paper is as follows. Section II introduces the eight-beta asset pricing framework. Section III describes the data. Section IV presents our empirical results for US data over the period 1929 to 2012, and Section V concludes.

II. Stock Fundamentals

This section first uses the log-linear approximation of unexpected excess returns as a sum of cash-flow and discount-rate news to obtain an intertemporal CAPM. It then explains how a VAR system can be employed to derive empirical proxies for aggregate and individual portfolio news components. In a second step, we discuss asymmetric preferences to motivate the use of downside risk in cross-sectional asset pricing. Finally, we show that a combination of these two approaches naturally gives rise to an eight-beta asset pricing relation that takes into account aversion related to downside movements in market-wide and firm-level news.

A. Cash-Flow and Discount-Rate Risks

The basic equation for stock returns relates unexpected changes in excess stock returns to expectations of future dividend growth and discount rates (Campbell and Shiller (1988) and Campbell (1991)):

$$r_{t+1} - E_t r_{t+1} \approx (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{1}$$

where r is the log excess stock return, d is log dividends, and E is the expectation operator. Here Δ denotes a one-period backward difference, while ρ is a log-linearization parameter; a number smaller but close to one. Equation (1) states that negative excess returns today should be associated with lower expected future dividend growth and/or higher expected future returns. Alternatively, the unexpected return component or return news, $N_{t+1} \equiv r_{t+1} - E_t r_{t+1}$, can be rewritten as a sum of cash-flow news $N_{c,t+1}$–corresponding to revision in expectations about future cash flows, i.e. dividend growth rates–and the discount-rate news $N_{d,t+1}$–corresponding to revision in expectations about future discount rates, i.e. returns: $N_{t+1} = N_{c,t+1} - N_{d,t+1}$.

Campbell (1991) assumes that the data follow a first-order vector autoregressive (VAR) process

$$\mathbf{z}_{t+1} = \mathbf{a} + \mathbf{A}\mathbf{z}_t + \mathbf{w}_{t+1} \tag{2}$$

where $\mathbf{z}_{t+1}$ is a m-by-1 state vector with r_{t+1} as its first element, $\mathbf{a}$ and $\mathbf{A}$ are m-by-1 vector and m-by-m companion matrix of constant parameters, and $\mathbf{w}_{t+1}$ is an i.i.d. m-by-1 vector of shocks. On can then easily show that the discount-rate news obeys

$$N_{d,t+1} = \mathbf{e1}'\mathbf{\Lambda}\mathbf{w}_{t+1}, \tag{3}$$

where $\mathbf{\Lambda} \equiv \rho\mathbf{A}\left(\mathbf{I} - \rho\mathbf{A}\right)^{-1}$ and $\mathbf{e1}$ denotes an m-by-1 vector whose first element is unity and the remaining elements are all zero. The cash-flow news can be then backed out as a residual

$$N_{c,t+1} = (\mathbf{e1}' + \mathbf{e1}'\mathbf{\Lambda})\,\mathbf{w}_{t+1}, \tag{4}$$

since both news terms sum up to the total news, N_{t+1}.

Campbell and Mei (1993) employ the return decomposition in Equation (1) to break the return on stock portfolios, sorted by industry or size, into cash-flow and discount-rate components: $N_{i,t+1} = N_{c_i,t+1} - N_{d_i,t+1}$. Campbell and Vuolteenaho (2004), by contrast, apply the return decomposition approach to the return on an aggregate stock index–an empirical proxy for a market portfolio–to disentangle market-wide cash-flow news and market-wide discount-rate news: $N_{m,t+1} = N_{c_m,t+1} - N_{d_m,t+1}$.

A log-linearized approximation of the intertemporal CAPM (ICAPM) of Merton (1973) suggests a higher compensation for assets' sensitivities to market cash-flow rather than discount-rate news. Campbell (1993) shows that the ICAPM can be interpreted in terms of preferences and parameters of consumption-based asset pricing models. In particular, he derives a closed-form solution for the consumption and portfolio choice problem by assuming that the variation in the consumption-wealth ratio is infinitely small. After substituting out consumption from a standard intertemporal asset pricing model, the risk premium on any asset i can be written as

$$E_t(r^e_{i,t+1}) = -\frac{Var_t(r_{i,t+1})}{2} + \gamma Cov_t(r_{i,t+1}, N_{m,t+1}) + (1-\gamma)Cov_t(r_{i,t+1}, -N_{d_m,t+1}), \tag{5}$$

where $r^e_{i,t+1}$ is the expected log excess return on any asset i over the riskless interest rate, $\frac{Var_t(r_{i,t+1})}{2}$ adjusts for Jensen's inequality, γ denotes the risk aversion parameter, $N_{m,t+1}$ is the unexpected return on the market portfolio, and $N_{d_m,t+1}$ is its time-varying discount-rate news as defined above. The first covariance term on the right-hand of Equation (5) corresponds to the myopic hedging component as in the static CAPM, while the second covariance term represents the intertemporal hedging motives of an asset holder as in the intertemporal CAPM of Merton (1973). Campbell and Vuolteenaho (2004) reformulate this equation to show that asset beta with the market cash-flow news should be rewarded with a greater premium than asset beta with the market discount-rate news. They therefore call the first beta "bad beta" computed as $\beta_{i,c} \equiv \frac{Cov_t(r_{i,t+1}, N_{c_m,t+1})}{Var_t(N_{m,t+1})}$ and the second beta "good beta" computed as $\beta_{i,d} \equiv \frac{Cov_t\left(r_{i,t+1}, -N_{d_m,t+1}\right)}{Var_t(N_{m,t+1})}$. Clearly, both betas sum up to the market beta computed as $\beta_{i,m} \equiv \frac{Cov_t(r_{i,t+1}, N_{m,t+1})}{Var_t(N_{m,t+1})}$. To test the relative importance of cash-flow and discount-rate news, Campbell and Vuolteenaho (2004) estimate the respective risk premia from a cross-sectional regression of the form

$$\overline{R_i^e} = \lambda_c \beta_{i,c} + \lambda_d \beta_{i,d} + e_i \tag{6}$$

where bar denotes time-series mean and $\overline{R_i^e} \equiv \overline{R_i} - R_f$ denotes the sample average excess return on asset i.

More recently, Campbell et al. (2010) combine the asset-specific with the market-wide return decompositions to propose a four-beta decomposition

$$\beta_{i,m} = \beta_{i,cc} + \beta_{i,dc} + \beta_{i,cd} + \beta_{i,dd} \tag{7}$$

where

$$\beta_{i,cc} \equiv \frac{Cov_t\left(N_{c_i,t+1}, N_{c_m,t+1}\right)}{Var_t\left(N_{m,t+1}\right)}, \tag{8}$$

$$\beta_{i,dc} \equiv \frac{Cov_t\left(-N_{d_i,t+1}, N_{c_m,t+1}\right)}{Var_t\left(N_{m,t+1}\right)}, \tag{9}$$

$$\beta_{i,cd} \equiv \frac{Cov_t\left(N_{c_i,t+1}, -N_{d_m,t+1}\right)}{Var_t\left(N_{m,t+1}\right)}, \tag{10}$$

$$\beta_{i,dd} \equiv \frac{Cov_t\left(-N_{d_i,t+1}, -N_{d_m,t+1}\right)}{Var_t\left(N_{m,t+1}\right)} \tag{11}$$

measure the sensitivities of stock-specific cash-flow and discount-rate news to the market-wide cash-flow and discount-rate news and $N_{m,t+1} = N_{c_m,t+1} - N_{d_m,t+1}$ as above. Campbell et al. (2010) show that the high "bad beta" of value stocks and the high "good beta" of growth stocks are driven by the cash-flow fundamentals of value and growth stocks. More generally, the authors argue that systematic risks of individual stocks are primarily driven by the systematic risks of their fundamentals. They hence conclude that growth stocks are not merely "glamour stocks" but reflect fundamental risks. Koubouros et al. (2010) explore the asset pricing implications of the four-beta decomposition by estimating separate risk prices for each of the components

$$\overline{R_i^e} = \lambda_{cc}\beta_{i.cc} + \lambda_{dc}\beta_{i,dc} + \lambda_{cd}\beta_{i,cd} + \lambda_{dd}\beta_{i,dd} + e_i. \tag{12}$$

They find that permanent shocks to the aggregate market are the main determinant of the overall equity premium. Firms' cash-flow and discount-rate sensitivities to the permanent market news earn statistically significant risk premia, and the four-model improves the two-beta model of Campbell and Vuolteenaho (2004) in terms of statistical fit.

In this paper, we propose a natural extension of the beta-decomposition approach into eight components related to cash-flow and discount-rate news in market and individual portfolio returns. Our decomposition allows to take into account loss aversion associated with aggregate and firm-level returns. Moreover, it gives guidance for empirical asset pricing tests which have not been explored yet in the literature. We then employ an empirical approximation of the Merton's (1973) ICAPM to test the cross-sectional implications of the eight-beta decomposition. We argue that recognizing the upside and downside components in market-wide and firm-level permanent and transitory components is crucial for understanding of assets' risk exposure.

B. Loss Aversion and Asymmetric Preferences

The notion of loss aversion or investors' asymmetric preferences with respect to downside losses as opposed to upside gains dates back to Roy (1952) and Markowitz (1952). Loss aversion as a risk concept is consistent with the way investors perceive losses as a failure to earn some minimum or target return (Hogan and Warren (1974)). In terms of equilibrium portfolio selection models, given a target return such as a risk-free interest rate or the return on a well-diversified market portfolio, assets with high sensitivity to (downside) realizations below the target demand a premium, while assets with high sensitivity to (upside) realizations above the target reflect a discount. Harlow and Rao (1989) generalize the downside risk literature by specifying risk as deviations from any arbitrary target rate of return. They show that the standard CAPM does not pass empirical tests, while their model with downside risk investors cannot be rejected against an unspecified alternative for a large set of target rates of return.

In line with these studies, Gul (1991) specifies a utility function which takes into account disappointment aversion reflected in agents' asymmetric perception of losses relative to gains. Proxying total wealth by a broad-based market portfolio of stocks we follow Ang et al. (2006) to summarize asymmetric preferences as

$$U(\overline{M}) = \widetilde{\Gamma}\left(\int_{-\infty}^{\overline{M}} U(M)dF(M) + \Gamma\int_{\overline{M}}^{\infty} U(M)dF(M)\right), \tag{13}$$

where $U(M)$ is the instantaneous utility function over the total market portfolio, e.g. a CRRA or power utility function, the parameter Γ is the coefficient of disappointment aversion, $F(\cdot)$ is the cumulative distribution function of market wealth, $\overline{M}$ is the certainty equivalent, and $\widetilde{\Gamma}$ is a scalar equal to the weighted probability of the downside and upside market wealth realizations:

$$\widetilde{\Gamma} = \Pr(M \leq \overline{M}) + \Gamma \Pr(M > \overline{M}). \tag{14}$$

Given $0 < \Gamma \leq 1$, agents place a greater weight to downside relative to upside market outcomes. Clearly, $\Gamma = 1$ implies a special case of a standard CRRA or the mean-variance utility. A similar logic underlies a theoretical model of equilibrium in capital markets with upside and downside betas of Bawa and Lindenberg (1977). In their framework, the traditional equilibrium CAPM also emerges as a special case which guarantees that downside risk models do at least as well in explaining market data as the standard asset pricing model.

Indeed, several studies provide empirical support for models featuring loss aversion. For example, Ang et al. (2006) find a cross-sectional equity premium for sensitivity to downside market movements of about 6% per annum in the post-1963 period. More recently, Botshekan et al. (2013) propose a four-way decomposition of the market beta which separates between upside and downside "bad" and "good" betas in the sense of Campbell and Vuolteenaho (2004):

$$\overline{R_i^e} = \lambda_c^+ \beta_{i.c}^+ + \lambda_c^- \beta_{i.c}^- + \lambda_d^+ \beta_{i.d}^+ + \lambda_d^- \beta_{i.d}^- + e_i. \tag{15}$$

In Equation (15), the upside and downside cash-flow and discount-rate betas are defined as

$$\beta_{i,c}^+ \equiv \frac{Cov_t\left(r_i, N_{c_m} \left| N_m > 0\right.\right)}{Var_t\left(N_m \left| N_m > 0\right.\right)}, \tag{16}$$

$$\beta_{i,c}^- \equiv \frac{Cov_t\left(r_i, N_{c_m} \left| N_m \leq 0\right.\right)}{Var_t\left(N_m \left| N_m \leq 0\right.\right)}, \tag{17}$$

$$\beta_{i,d}^+ \equiv \frac{Cov_t\left(r_i, -N_{d_m} \left| N_m > 0\right.\right)}{Var_t\left(N_m \left| N_m > 0\right.\right)}, \tag{18}$$

$$\beta_{i,d}^- \equiv \frac{Cov_t\left(r_i, -N_{d_m} \left| N_m \leq 0\right.\right)}{Var_t\left(N_m \left| N_m \leq 0\right.\right)}, \tag{19}$$

respectively. The authors document large risk premia for downside cash-flow risk in a cross section of US common stocks traded on the NYSE, AMEX, and NASDAQ exchanges. In a related study, Galsband (2012) finds evidence on the downside risk exposure of international stock returns in fourteen major industrialized economies around the world. She shows that differences in returns on value and growth portfolios are largely attributed to assets' reagibilities to market's downside shocks: International value (growth) stock returns are determined by the market's permanent (temporary) downside shocks. This literature, however, leaves unexplored whether the downside betas of value and growth stocks with the market are caused by assets' cash-flow or discount-rate components–a question we address in this paper.

C. Eight-Beta Decomposition

The importance of firm-level fundamentals has been highlighted by Campbell et al. (2010) who show that high sensitivities of value (growth) stocks to the market's cash-flow (discount-rate) shocks can be driven back to the cash-flow fundamentals of value and growth companies. Ang et al. (2006), among others, emphasize the role of asymmetric preferences for understanding of common variation in stock prices.

In this paper, we combine the two views and ask whether firms' downside risks with market cash flows are determined by the characteristics of firms' cash flows, or whether they are instead driven by changes in firms' opportunity cost of capital investors apply to value assets. To approach this issue, we break the beta of a stock with the market portfolio into eight components related to future market-wide and firm-level cash flows and discount rates in up and down markets:

$$\beta_{i,cc}^{+} \equiv \frac{Cov_t\left(N_{c_i}, N_{c_m} \left| N_m > 0\right.\right)}{Var_t\left(N_m \left| N_m > 0\right.\right)}, \tag{20}$$

$$\beta_{i,dc}^{+} \equiv \frac{Cov_t\left(-N_{d_i}, N_{c_m} \left| N_m > 0\right.\right)}{Var_t\left(N_m \left| N_m > 0\right.\right)}, \tag{21}$$

$$\beta_{i,cd}^{+} \equiv \frac{Cov_t\left(N_{c_i}, -N_{d_m} \left| N_m > 0\right.\right)}{Var_t\left(N_m \left| N_m > 0\right.\right)}, \tag{22}$$

$$\beta_{i,dd}^{+} \equiv \frac{Cov_t\left(-N_{d_i}, -N_{d_m} \left| N_m > 0\right.\right)}{Var_t\left(N_m \left| N_m > 0\right.\right)}, \tag{23}$$

$$\beta_{i,cc}^{-} \equiv \frac{Cov_t\left(N_{c_i}, N_{c_m} \left| N_m \leq 0\right.\right)}{Var_t\left(N_m \left| N_m \leq 0\right.\right)}, \tag{24}$$

$$\beta_{i,dc}^{-} \equiv \frac{Cov_t\left(-N_{d_i}, N_{c_m} \left| N_m \leq 0\right.\right)}{Var_t\left(N_m \left| N_m \leq 0\right.\right)}, \tag{25}$$

$$\beta_{i,cd}^{-} \equiv \frac{Cov_t\left(N_{c_i}, -N_{d_m} \left| N_m \leq 0\right.\right)}{Var_t\left(N_m \left| N_m \leq 0\right.\right)}, \tag{26}$$

$$\beta_{i,dd}^{-} \equiv \frac{Cov_t\left(-N_{d_i}, -N_{d_m} \left| N_m \leq 0\right.\right)}{Var_t\left(N_m \left| N_m \leq 0\right.\right)}. \tag{27}$$

We employ an empirical approximations of the ICAPM of Merton (1973) to test the asset pricing implications of the eight-beta decomposition:

$$\overline{R_i^e} = \lambda_{cc}^{+}\beta_{i,cc}^{+} + \lambda_{cc}^{-}\beta_{i,cc}^{-} + \lambda_{cd}^{+}\beta_{i,cd}^{+} + \lambda_{cd}^{-}\beta_{i,cd}^{-} + \lambda_{dc}^{+}\beta_{i,dc}^{+} + \lambda_{dc}^{-}\beta_{i,dc}^{-} + \lambda_{dd}^{+}\beta_{i,dd}^{+} + \lambda_{dd}^{-}\beta_{i,dd}^{-} + e_i. \tag{28}$$

To estimate the factor prices the portfolio betas, we use a two-stage procedure outlined in Fama and MacBeth (1973). In the first stage, for each portfolio i, we run a time-series regression of cash-flow or the negative of discount-rate news on portfolio i, N_{c_i} or $-N_{d_i}$, on the market cash-flow or the negative of market discount-rate news, N_{c_m} or $-N_{d_m}$, for upside and downside markets separately. Periods with total market news above (below) its mean are defined as upside (downside) markets. We then scale the obtained slope coefficient appropriately to arrive at the beta estimates in Equations (20)-(27). In the second stage, we run a cross-sectional regression of average excess returns $\overline{R_i^e}$ on the estimated betas to arrive at the factor prices. Standard errors are adjusted for the fact that the regressors are generated in line with Shanken (1992).

III. Data

Our empirical analysis is conducted on US data sampled at monthly frequency. This section first summarizes the properties of test asset returns and then turns to state variables employed for the estimation of news series.

A. Portfolio Data

Two sets of benchmark value-weight stock portfolio returns are employed in this study. The first is a set of 25 double-sorted portfolios, the second is a set of 30 single-sorted portfolios.

These data are constructed by Eugene F. Fama and Kenneth R. French and freely available in the online library of Kenneth R. French. The sample period is monthly running from January 1929 to September 2012.

A.1. 25 Double-Sorted Portfolios

The portfolios are formed from an independent sort of all stocks in NYSE, AMEX, and Nasdaq in the CRSP Monthly Stock Database into quintiles based on size, i.e. market equity, and the ratio of book equity to market equity. The portfolios are constructed at the end of June of each calendar year as intersections of five size (S) and five book-to-market (B) portfolios. For example, small growth portfolio is denoted by S1B1 and big value portfolio is denoted by S5B5. The market equity is the market capitalization at the end of June. The book-to-market ratio is computed as a ratio of book equity at the last fiscal year end of the prior calendar year divided by market equity at the end of December of the prior year. Firms with negative book equity are not included in any portfolio. Due to their stable properties across different samples and frequencies, these portfolios are typically used in the literature to examine the performance of various asset pricing models. Table 1 shows a substantial dispersion in the average excess returns across the 25 portfolios. Stocks with lowest book-to-market equity realized excess returns between 4.68 and 7.61 percent per year while stock with highest book-to-market equity earn on average between 10.21 and 15.91 percent per year. The return differential between value and growth stocks varies from 3.79 percent per year for biggest size category stocks to 11.25 percent per year for smallest size category stocks. In line with Fama and French (2012), the value premium is declining with size. Furthermore, small stocks on average outperform big stocks within the same book-to-market quintile, except for small growth stocks.

[about here: Table 1]

A.2. 30 Single-Sorted Portfolios

In addition, we use a second set of assets consisting of 10 size-, 10 book-to-market- and 10 past performance or momentum sorted portfolios of the same stocks traded in NYSE, AMEX, and Nasdaq. Our rationale for considering these portfolios is that firm characteristics related to size, book-to-market, and momentum build the basis for three- and four-factor models in Fama and French (1993) and Carhart (1997) to explain returns on other assets.

B. VAR State Variables

We work with both aggregate and firm-specific variables as the elements of the state vector. In the following we describe these data.

B.1. Aggregate VAR

In specifying the aggregate VAR, we choose a state vector consisting of four variables: excess market return, the small-stock value spread, the market's smoothed price-earnings ratio, and short term interest rate. The methodology outlined in Section II requires the first element to be the excess market return. As an empirical proxy, the literature typically employs the difference between the log return on the CRSP value-weight index and the log risk-free rate. The excess return series is provided in the online data library of Kenneth R. French.

The second variable, small-stock value spread, is motivated by the ICAPM itself (see Campbell and Vuolteenaho (2004)). Further studies suggest that growth stocks payoff in a distant future or depend heavily on external financing and are therefore particularly exposed to fluctuations in equity market conditions. This series are also calculated from data made available by Kenneth R. French on his web site. The appendix to Campbell and Vuolteenaho (2004) presents further details on construction of this variable.

The third variable, the log smoothed market's price-earnings ratio, is motivated in Campbell and Vuolteenaho (2004) by the low predictability of earnings growth. To circumvent cyclical spikes in earnings, this variable is constructed from the data provided on the web site of Robert Shiller as the log ratio of the S&P 500 price index to a ten-year moving average of the S&P 500 earnings. Campbell and Vuolteenaho (2004) include additionally the yield spread between long-term and short-term bonds in the state vector. Over our sample period, this variable is, however, insignificant and we exclude it from the state vector. None of our conclusions appear affected by this omission. In particular, we obtain qualitatively similar results if we stick with the original Campbell and Vuolteenaho (2004) specification.

Finally, we follow Botshekan et al. (2013) and Ang and Bekaert (2007) to include the short term interest rate as the fifth element of the VAR system. The data on the annualized risk-free rate is available in the online library of Kenneth R. French.

Several recent studies argue that it is important to include dividend yield as a state variable. The use of dividend yield as a predictor of excess stock returns is motivated theoretically (Campbell and Shiller (1988)) and empirically (Ang and Bekaert (2007)). None of our conclusions change once we additionally introduce the dividend yield as fifth state variable. However, we find that the price-earnings ratio has a stronger forecasting ability for excess returns than the dividend yield. In particular, if both price-earnings ratio and dividend yield enter the return forecasting equation, the coefficient on the dividend yield turns significantly negative while the price-earnings ratio pertains its power. For this reason, we opt for not including the dividend yield in our benchmark specification but explore its role in details in the next section.

Table 2 reports the benchmark characteristics of the first-order VAR model including a constant, log excess market return, small-stock value spread, price-earnings ratio, and a short-term interest rate for the sample period from December 1928 to September 2012. The VAR is estimated using OLS and employing $\rho = 0.9957$. Each row of Table 2 corresponds to a different dependent variable listed in the header of the row. OLS t-statistics are reported in parentheses below the coefficient estimates. The first six columns report coefficients on a constant and five explanatory variables listed in the column header; the last column gives the adjusted $\overline{R}^2$ statistics. The correlation between the implied cash-flow news and the discount-rate news is -0.20.

[about here: Table 2]

The top row of Table 2 is indicative of the forecasting potential of state variables for market returns.[1] As documented in the earlier literature, the momentum property is strongly pronounced for monthly returns. In line with previous studies, the past small-stock value spread negatively forecasts the stock market with a t-statistic of 2.44. Former research indicates that a higher price-earnings ratio is associated with lower returns. Our estimation strongly supports this result. Finally, the short term interest rate negatively predicts returns in line with Ang and Bekaert (2007) and Botshekan et al. (2013). The $\overline{R}^2$ statistic for the return equation is 2.40% which appears a plausible number for a monthly sample.

The next rows summarize the forecasting power of the VAR system for the remaining state variables. Overall, $\overline{R}^2$ statistics are high and the autoregressive coefficients are all very close to unity which raises some difficult statistical issues (e.g. Campbell et al. (2010)); caution is appropriate when interpreting the results.

B.2. Firm-Level VAR

In our benchmark specification, we employ firm characteristics to forecast portfolio returns. Our robustness analysis tests the sensitivity of our conclusions when aggregate market state variables enter both market-wide and firm-level VARs. Our main conclusions remain qualitatively similar in both cases and hence cannot be attributed to the set of variables in the system.

For the main specification of the firm-level VAR, the following three state variables are employed. The first is the log value-weighted portfolio return. Following Campbell et al. (2010), we use market-adjusted returns obtained by subtracting the market return from the

[1] The appendix of Campbell and Vuolteenaho (2004) warns that the interpretation of persistent coefficients depends on the correlation structure of innovations in forecasting variables with unexpected returns. In our case, this concern applies to the errors in price-earnings ratio which reveal a correlation of beyond 0.7 with the unpredicted component in the market return.

portfolio return in each time period. The market return is the return on the value-weight CRSP index. The second state variable is the log book-to-market equity ratio, measured as a value-weighted average of book-to-market equity of all stocks in the portfolio. We used an alternative measure of book-to-market equity–calculated as a ratio of the sum of book equities to the sum of market equities of all stocks in the portfolio–interchangeably and obtained similar results. We include this variable in the VAR to capture the well-known value effect in returns (Graham and Dodd (1934)). The third state variable is the log market equity, measured as the sum of market equities of all stocks in the portfolio. This variable enters the VAR to control for the size effect in financial market data (Banz (1981)).

We estimate a separate VAR system for each portfolio. We summarize the outcome as follows. There is a modest degree of momentum in monthly individual stock returns. The book-to-market equity typically positively predicts future returns. By contrast, the coefficient on the market equity changes sign and is mostly insignificant. This observation is related to a declining size effect documented by Horowitz et al. (2000).

IV. Empirical Evidence

In this section, we summarize our empirical findings. We start by discussing the cross-sectional evidence and compare the performance of the eight-beta model with other popular return decompositions. We then explore the risk premium contributions of each risk component to average excess returns on value and growth portfolios. Finally, we present an extensive sensitivity analysis.

A. Baseline Risk Premia Estimates

Table 3 summarizes our main results. It presents the second-stage Fama-MacBeth (1973) estimates in percent per annum when using 25 size- and book-to-market sorted portfolios as test assets. The estimated models are (i) the standard CAPM, (ii) the two-beta ICAPM with cash-flow and discount-rate risks proposed by Campbell and Vuolteenaho (2004), (iii) the four-beta ICAPM with market and firm-level cash-flow and discount-rate risks proposed by Campbell et al. (2010), (iv) the four-beta ICAPM with upside and downside cash-flow and discount-rate risks proposed by Botshekan et al. (2013), and (v) the eight-beta ICAPM with upside and downside market-wide and firm-level cash-flow and discount-rate risks proposed in this paper. For each model, it gives the estimated risk premia along with Shanken (1992) corrected t-statistics in parentheses, the associated R^2 corrected for degrees of freedom, as well as the mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum. The sample period of returns covers January 1929 to March 2012.

[about here: Table 3]

Our main findings are easily summarized. The standard static CAPM of Sharpe (1964) and Lintner (1965) fails disastrously in explaining the cross-sectional variation in average returns (Fama and French (1992)). The price of market risk is estimated with a large error, and the poor model fit is reflected in a low R^2 of less than 4.5%. The poor model fit translates in a total mean squared pricing error exceeding the annual risk premium.

There is a substantial improvement in terms of general fit once time-variation in discount rates is taken into account as in the two-beta ICAPM version of Campbell and Vuolteenaho (2004). The specification in column (ii) explains about 28% of the cross-sectional dispersion in stock returns. Campbell and Vuolteenaho (2004) report measures of fit of roughly 50% for the sample period 1963-2001. Our estimates over the post-1963 period support higher adjusted R^2 measures of up to 46%. The estimated risk premium for market cash-flow news is about 35% p.a. over the period 1929-2012 and is close to 70% p.a. for the 1963-2012 sample. Campbell and Vuolteenaho (2004) report estimates of a similar order of magnitude. In line with previous findings, there are large standard errors associated with these estimates. However, the cash-flow premium is significantly different from zero, in contrary to the discount-rate premium estimates. Campbell and Vuolteenaho (2004) show that differences in so called "bad" cash-flow betas can largely explain the pattern in average stock returns on value and growth portfolios in the post-1963 period. More recently, Galsband and Nitschka (2013) employ the two-beta model to study common determinants behind equity and foreign exchange markets. They find that the failure of the uncovered interest rate parity (UIP) can be partly rationalized by currency investment sensitivities to the stock market cash-flow news.

Column (iii) summarizes baseline risk premia estimates of a four-beta model in Campbell et al. (2010) evaluated in Koubouros et al. (2010). Campbell et al. (2010) argue that firm–level shocks constitute an important risk characteristics on top of market news. The authors show that value and growth stocks' fundamentals are responsible for assets' sensitivities to market's cash-flow and discount-rate shocks. Consistent with the theory, our estimates support a significant risk premium for sensitivities to market cash-flow shocks. In line with Koubouros et al. (2010), we find higher risk premia for assets' comovement with market cash flows (λ_{cc} and λ_{dc}) than for assets' reagibilities to market discount rates (λ_{cd} and λ_{dd}). The model fit of about 55% is reasonable and broadly of the same order of magnitude as previously documented.

The four-beta ICAPM of Botshekan et al. (2013) in column (iv) generates a similar general fit but slightly lower pricing errors. It reveals two additional important insights about the determination of risk premia on equity markets. First, the cross-section of returns reflects a downside risk exposure. Secondly, both the downside cash-flow and the downside discount-rate obtain a significant compensation with the former exceeding the latter. In line with other studies, we find that the downside cash-flow beta carries the largest premium. Interestingly, this conclusion obtains for a VAR specification with dividend yield (e.g. Botshekan et al. (2013)) and without this variable (e.g. Galsband (2012)).

Finally, column (v) summarizes the results for our new eight-beta decomposition. Our key finding is that systematic risks embodied in stocks' cash-flow sensitivities to permanent aggregate shocks during market declines command a positive and highly significant premium. This result survives a battery of robustness checks we discuss below. The risk premium associated with $\beta^-_{i,cc}$'s of 33% p.a. is high but in line with cash-flow premia reported in the finance literature. Furthermore, our estimates support the importance of downside risk in asset pricing: The coefficients of λ^-_{cc}, λ^-_{cd}, λ^-_{dc}, and λ^-_{dd} are estimated highly significantly, albeit the estimates of λ^-_{cd} and λ^-_{dd} are negative. Chen and Zhao (2009), among others, document negative risk premia associated with market discount rates.

The estimates in Table 3 arise from market-wide cash-flow and discount-rate news obtained from a VAR including market return, value spread, price-earnings ratio and the riskless interest rate summarized in Table 2. The firm-level cash-flow and discount-rate news terms are estimated in a separate VAR relying on excess portfolio return, portfolio book-to-market equity, and average firm size. In an extensive analysis, we document that changes in specification (e.g. with respect to the vector of state variables, test assets or sample period choice) can affect the estimates of premia associated with λ^-_{cd}, λ^-_{dc}, and λ^-_{dd} quite substantially. Depending upon specification, λ^-_{cd}, λ^-_{dc}, and λ^-_{dd} switch signs and are instable in statistical terms. In stark contrast to this result, we find that firm's cash-flow sensitivities to downside aggregate market cash flows remain the main driver behind the cross-section of stock excess returns. This point becomes particularly striking in the post-1963 period when cross-sectional differences in $\beta^-_{i,cc}$'s emerge as the only source of equity premium. An additional important point concerns the overall model fit. The eight-beta decomposition explains robustly a large part of cross-sectional risk premia with an adjusted R^2 measure of about 90%. Across different specifications, the R^2 statistic lies typically in the range between 80% and 90% but never drops below the 60% mark. Finally, our model generates significantly lower pricing error compared to benchmark models in columns (i)-(iv). In particular, the squared pricing error is about 14 times smaller than in the case of static CAPM and more than 5 times smaller than in the case of four-beta empirical ICAPM approximations–the point we highlight in the next subsection

In sum, our results emphasize the importance of downside fluctuations in the slow-moving persistent component of fundamentals in understanding the risk exposure of assets. This finding contributes to a large body of studies in financial economics–initiated by Bansal and Yaron (2004) and continued by Parker and Julliard (2005), Bansal et al. (2005), Jagannathan and Wang (2007), Da (2009), and many others–pointing towards long-run risks as the key determinant of expected returns.

B. Pricing Errors

In this subsection, we take a closer look at the pricing errors generated by the static CAPM as well as the discrete time versions of the Merton's (1973) ICAPM. Table 4 reports the individual pricing errors for each model we investigate in percent per annum from the Fama-MacBeth regressions presented in Table 3. The table lists the errors for each of the 25 size and book-to-market sorted Fama-French portfolios. S1 denotes portfolios with the smallest firms (measured by the market equity), and S5 includes portfolios with largest firms. Similarly, B1 refers to portfolios with lowest book-to-market ratio firms–labeled as "growth stocks", and B5 includes portfolios with the highest book-to-market equity firms–labeled as "value stocks".

[about here: Table 4]

Column (i) in Table 4 reports the individual portfolio pricing errors generated by the standard CAPM. Lettau and Ludvigson (2001) note that the main source of the failure of the CAPM is the mispricing of portfolios for extreme growth (B1) and extreme value (B5) stocks within the same size category. Within each size category, the CAPM predicts the largest errors for S1B1 and S1B5, S2B1 and S2B5, and S3B1 and S3B5. For each of these three pairs, B5 stocks earn higher average returns than B1 stocks but their market betas are of similar size. Hence, the CAPM overpredicts average returns on growth stocks and underpredicts average returns on value stocks. This explains negative errors for B1 portfolios and positive errors for B5 portfolios. In fact, this regularly is also pronounced for the remaining two pairs, S4B1 and S4B5, and S5B1 and S5B5, albeit less strongly. In a cross-section of the five models presented in Table 4, the CAPM tends to produced the largest errors in absolute values for 11 out of 25 portfolios including S1B1, S1B5, S2B1, S2B4, S2B5, S3B1, S3B4, S4B1, S4B4, S5B1, and S5B2.

Column (ii) shows that the two-beta ICAPM also has difficulties in fitting the data precisely. In general, the pricing errors in column (ii) are lower than in column (i) but substantially higher than in columns (iii)-(v). Similar to the static CAPM, the two-beta ICAPM as well as the four-beta ICAPM in column (iii)–albeit to a smaller extent–have low power in explaining the value effect in the data. The four-beta representation which distinguishes between upside and downside risks as well as our eight-beta decomposition with market-wide and firm-level upside and downside betas tend to do better in this respect. In general, however, the eight-beta model tends to strongly outperform other standard benchmark models. In a cross-section of the five models summarized here, the eight-beta decomposition produces the lowest errors in roughly a half of all portfolios.

C. Risk Premia Contributions

Our findings in previous subsections highlight the statistical importance of comovement between market's and stocks' cash flows in times of bear markets for the cross-section of value and growth portfolios in the data. Economically, this result can be attributed to (i) differences in downside cash-flow betas of US firms to aggregate market cash-flow news, (ii) high risk premium estimates associated with these betas or both. To investigate this question, we perform an overlapping rolling window analysis in the style of Cochrane (2005).

To alleviate any concerns that our results are due to the assumption of fixed betas over the evaluation period, we relax this constrain in this subsection. Instead of constant betas, an alternative approach to asset pricing assumes that betas change continuously during the sample period. Time-variation in betas makes it possible to perform an in- (and later an out-of-) sample Fama-MacBeth (1973) two-stage analysis with over time changing betas estimated using overlapping rolling windows.

We proceed as follows. First, for each month t, we estimate the eight betas defined in Equations (20)-(27) for each test asset separately in a recursive manner over the subsample of a rolling window interval. For instance, the first 90-month window spans January 1929 to June 1936 and the last April 2005 to September 2012; so we analyze 916 overlapping 90-month windows in total. Second, each month we run a cross-sectional regression of average returns over the same rolling window on the estimated betas. In this way, we can compute a time series of the risk premia components which correspond to the eight types of time-varying betas. Table 5 presents the cross-section of $\beta^+_{i,cc}$, $\beta^-_{i,cc}$, $\beta^+_{i,cd}$, $\beta^-_{i,cd}$, $\beta^+_{i,dc}$, $\beta^-_{i,dc}$, $\beta^+_{i,dd}$, and $\beta^-_{i,dd}$'s computed as time-series averages of the respective betas over the 90-month rolling windows. The pattern in full sample betas strongly reminds of the pattern in average time-varying betas, however, one important advantage of the rolling-window analysis is that it takes into account any changing property of a series over time and diversifies away non-systematic effects in the data by averaging over the number of intervals.

[about here: Table 5]

The structure of the betas matrix in Table 5 is similar to the presentation in Table 1. In line with the previous notation, S1 denotes the lowest market equity quintile, S5 the highest market equity quintile, B1 the lowest book-to-market equity quintile, and B5 the highest book-to-market equity quintile. The firm-level and aggregate market news components are as in our benchmark case discussed in Table 3. Column B5–B1 at the right edge reports differences between extreme value and extreme growth in each size category. Table 5 reveals a number of interesting observations.

First, value firms' cash flows have a stronger tendency to comove with market-wide cash flows than growth stocks' cash flows. This finding is generally true and provides further support to Campbell et al. (2010). It pertains to both upside and downside market fluctuations. Extreme value portfolios have high (positive) $\beta^+_{i,cc}$'s and $\beta^-_{i,cc}$'s. In stark contrast, extreme growth portfolios have low (negative) $\beta^+_{i,cc}$'s and $\beta^-_{i,cc}$'s. We take this to be evidence that firms' cash-flow sensitivities to market's cash flows are the drivers behind the cross section of average returns of stock portfolios formed on size and book-to-market equity ratio. Moreover, growth stocks tend to offer insurance, while value stocks hide statistically grounded exposures to fluctuations in permanent shocks. Both $\beta^{+}_{i,cc}$'s and $\beta^{-}_{i,cc}$'s can be informative about the general pattern in average returns and the risk-return trade-off on equity markets.

Second, there is an opposite pattern in sensitivities of assets' cash flows to the aggregate market discount rates. The estimates of $\beta^{+}_{i,cd}$'s and $\beta^{-}_{i,cd}$'s suggest that growth stocks' fundamentals hide a greater reagibility to the market's discount-rates than the respective value stocks' fundamentals. This point underpins Campbell et al. (2010) who argue that growth stocks are not merely "glamour stocks" whose systematic risks are driven by investor sentiment. We find that the systematic risks of low book-to-market firms are primarily due to the systematic risks of their fundamentals.

Finally, firms' discount rates have generally very low and often zero sensitivities to market's discount-rate news. This observation holds true for $\beta^{+}_{i,dc}$, $\beta^{-}_{i,dc}$, $\beta^{+}_{i,dd}$, as well as $\beta^{-}_{i,dd}$'s, for both value and growth stocks, in upside and downside markets. Firms' discount rates appear less informative about systematic differences in returns on value and growth stocks in contrast to firms' cash flows. This results emphasizes that systematic risks embodied in stocks' cash flows are the key in understanding the risk exposure of assets. This is one of our central insights.

To further explore this issue, Table 6 displays the average equity premium contributions of the eight risk factors explored in this paper. We obtain the average contributions of $\lambda^{+}_{cc}\beta^{+}_{i,cc}$, $\lambda^{-}_{cc}\beta^{-}_{i,cc}$, $\lambda^{+}_{cd}\beta^{+}_{i,cd}$, $\lambda^{-}_{cd}\beta^{-}_{i,cd}$, $\lambda^{+}_{dc}\beta^{+}_{i,dc}$, $\lambda^{-}_{dc}\beta^{-}_{i,dc}$, $\lambda^{+}_{dd}\beta^{+}_{i,dd}$, and $\lambda^{-}_{dd}\beta^{-}_{i,dd}$'s to the total average equity premium as time-series averages of the respective $\lambda^{\cdot}_{jt}\overline{\beta^{\cdot}_{i,jt}}$ products where $\overline{\beta^{\cdot}_{i,jt}}$ is the cross-sectional mean of beta of upside or downside component of risk factor j over the 90-month rolling window in month t, and $\lambda^{\cdot}_{jt}$ is the estimated risk premium for upside or downside component of risk factor j from monthly recursive cross-sectional regressions of average returns over the 90-month rolling window t on a constant and betas over the same rolling window. To compute the cross-sectional betas $\overline{\beta^{\cdot}_{i,jt}}$, specification (i) relies on a large pool of all 25 size- and book-to-market portfolios; specification (ii) considers the five extreme value portfolios with the highest book-to-market ratios; and specification (iii) averages across five extreme growth portfolios with the lowest book-to-market ratios.

[about here: Table 6]

Table 6 highlights a number of important points. First, column (i) demonstrates that over the complete sample period 1929-2012 firms' fundamentals embodied in value and growth portfolios' cash flows contribute much stronger to the total equity premium than firms' discount rates, i.e. $\lambda_{cc}^{+}\beta_{i,cc}^{+}$, $\lambda_{cc}^{-}\beta_{i,cc}^{-}$, $\lambda_{cd}^{+}\beta_{i,cd}^{+}$, and $\lambda_{cd}^{-}\beta_{i,cd}^{-}$'s exceed $\lambda_{dc}^{+}\beta_{i,dc}^{+}$, $\lambda_{dc}^{-}\beta_{i,dc}^{-}$, $\lambda_{dd}^{+}\beta_{i,dd}^{+}$, and $\lambda_{dd}^{-}\beta_{i,dd}^{-}$'s, respectively. Furthermore, except for the risks associated with discount-rate sensitivities of firms to market's cash flows ($\lambda_{dc}^{+}\beta_{i,dc}^{+}$ and $\lambda_{dc}^{-}\beta_{i,dc}^{-}$), it generally holds true that risk exposure in downside markets is typically reflected in an economically higher total contribution than risk exposure in upside markets, i.e. $\lambda_{cc}^{-}\beta_{i,cc}^{-}$ is greater than $\lambda_{cc}^{+}\beta_{i,cc}^{+}$, $\lambda_{cd}^{-}\beta_{i,cd}^{-}$ is greater than $\lambda_{cd}^{+}\beta_{i,cd}^{+}$, and $\lambda_{dd}^{-}\beta_{i,dd}^{-}$ is greater than $\lambda_{dd}^{+}\beta_{i,dd}^{+}$. Most importantly, our results suggest that in a cross-section of value and growth portfolios the downside systematic risks embodied in stocks' cash-flow sensitivities to permanent aggregate shocks during market declines carry the highest premium.

Examining the rest of table reveals at least two further interesting insights. Common price movements in value and growth firms can be attributed to the observation that sensitivities related to firms' cash flows are generally more important for equity premium formation than sensitivities related to firms' discount rates. Columns (ii) and (iii) support that for both value as well as growth portfolios separately, it holds true that $\lambda_{cc}^{+}\beta_{i,cc}^{+}$ exceeds $\lambda_{dc}^{+}\beta_{i,dc}^{+}$, $\lambda_{cc}^{-}\beta_{i,cc}^{-}$ exceeds $\lambda_{dc}^{-}\beta_{i,dc}^{-}$, $\lambda_{cd}^{+}\beta_{i,cd}^{+}$ exceeds $\lambda_{dd}^{+}\beta_{i,dd}^{+}$, and $\lambda_{cd}^{-}\beta_{i,cd}^{-}$ exceeds $\lambda_{dd}^{-}\beta_{i,dd}^{-}$. Interestingly, columns (ii) and (iii) also point towards systematic differences in risk exposure of high and low book-to-market equity firms: Excess returns on value stocks are driven by their sensitivities to downside markets. Excess returns on growth stocks, in contrast, reflect their sensitivities to upside markets. Except for $\lambda_{cc}^{-}\beta_{i,cc}^{-}$ and $\lambda_{cc}^{+}\beta_{i,cc}^{+}$, value stocks receive greater premium components for $\lambda_{cd}^{-}\beta_{i,cd}^{-}$, $\lambda_{dc}^{-}\beta_{i,dc}^{-}$ and $\lambda_{dd}^{-}\beta_{i,dd}^{-}$'s than for $\lambda_{cd}^{+}\beta_{i,cd}^{+}$, $\lambda_{dc}^{+}\beta_{i,dc}^{+}$ and $\lambda_{dd}^{+}\beta_{i,dd}^{+}$'s. Higher total contribution for $\lambda^+_{cc}\beta^+_{i,cc}$ versus $\lambda^-_{cc}\beta^-_{i,cc}$ mirrors higher $\beta^+_{i,cc}$'s of extreme book-to-market stocks compared to their $\beta^-_{i,cc}$'s, even though λ^-_{cc} is generally associated with higher economic and statistically significant estimates as opposed to λ^+_{cc}. Finally, in contrast to value stocks, growth stocks premia are mainly associated with upside markets, i.e. $\lambda^+_{cc}\beta^+_{i,cc}$, $\lambda^+_{cd}\beta^+_{i,cd}$, $\lambda^+_{dc}\beta^+_{i,dc}$ and $\lambda^+_{dd}\beta^+_{i,dd}$'s exceed economically $\lambda^-_{cc}\beta^-_{i,cc}$, $\lambda^-_{cd}\beta^-_{i,cd}$, $\lambda^-_{dc}\beta^-_{i,dc}$ and $\lambda^-_{dd}\beta^-_{i,dd}$'s, respectively, for firms with lowest book-to-market ratios.

D. Robustness Analysis

This section provides details on robustness checks. We investigate the sensitivity of our eight-beta model to a broad range of alternative choices of various state variables. We include both firm characteristics and economic aggregates such as dividend yields, simple and relative risk-free rate, term yield and default spreads in the vector of state variables. We employ an alternative estimation technique which allows to calculate the cash-flow news directly and independently of the discount-rate news. We work with other test assets such as 10 size-, 10 book-to-market-, and 10 past performance sorted portfolios or 30 industry-sorted portfolios. We allow for various thresholds for downside versus upside risks, change the sample period, control for size and value effects, change the value of the linearization parameter, and explore the in- and out-of-sample properties of the model. Our tests confirm the importance of downside fluctuations in the slow-moving persistent component of fundamentals in understanding the risk exposure of assets.

D.1. Dividend Yield and Variation in the Set of State Variables

The importance of the dividend yield for the precision of the VAR forecasts is emphasized in Campbell et al. (2010), Engsted et al. (2012), and Chen and Zhao (2009) on theoretical grounds and based on the strong empirical ability of the dividend yield to produces unbiased news forecasts. Chen and Zhao (2009) show that the return decomposition approach in Campbell and Shiller (1988) and Campbell (1991) can be sensitive the choice of state variables. Our benchmark VAR model includes excess returns, small-stock value spread, the price-to-earnings ratio, and the interest rate. Experiments with a fifth variable, the dividend yield, lead to qualitatively similar, often even slightly stronger conclusions. However, a return predicting equation which includes both price-to-earnings ratio and the dividend yield generalizes implausible estimates on the dividend yield. In general, we find that over our sample period, the price-to-earnings ratio beats different measures of dividend yield and do not include the latter in the vector of benchmark state variables.

To address the concern of Chen and Zhao (2009), this subsection discusses several VAR specifications which include the dividend yield to demonstrate that our conclusions are unaffected by this assumption. Table 7 gives the cross-sectional estimates for three sets of set variables. To extract market cash-flow and discount-rate news, specification (i) differs from our benchmark specification by replacing the price-earnings ratio with the dividend yield computed from the data set of Robert Shiller as a difference between log real dividends and log real prices on the S&P 500 index. Specification (ii) employs a different measure of dividend yield based on a twelve-month trailing average. Finally, specification (iii) uses a measure of dividend yield computed as a ratio of previous period dividend to current stock price. As in the baseline case, we estimate portfolio-specific cash-flow and discount-rate news terms separately in a VAR with firm-level characteristics. We relax this assumption subsequently.

[about here: Table 7]

We find that minor changes in the VAR specification have no strong effect on the estimates. In particular, the estimate of λ^{-}_{cc} remains a significant determinant of average returns on value and growth portfolios. Two other downside risk exposures (λ^{-}_{cd} and λ^{-}_{dd}) are priced, albeit with a negative sign. The model's explanatory power is robust with an adjusted R^2 of about 90%. Most importantly, our empirical evidence supports the view that differences in the sensitivities of firms' cash flows to permanent market shocks in times of market decline are the key to rationalize the cross-sectional dispersion in average stock returns. This relation is unaffected by different proxies of the dividend yield and minor variation in the vector of state variables.

In a next exercise, summarized in Table 8, we follow Koubouros et al. (2010) and employ the same set of state variable to extract both market-wade and portfolio-specific news components. Again we consider three alternative sets of state variables in line with Table 7. Our estimates suggest that this design favours risks associated with the response of firms' discount-rate shocks to permanent innovations in market returns both in times of bear and bull markets. However, our findings further underpin the importance of downside fluctuations in the slow-moving persistent component of fundamentals across all specifications.

[about here: Table 8]

Finally, we examine the robustness of our benchmark results to alternative firm-level state variables. Following the benchmark case, we compute the market-wide news from a VAR presented in Table 2. To calculate the firm-level news, Table 8 relies on three sets of firm-specific characteristics. Specification (i) includes excess portfolio return, portfolio book-to-market equity and average firm size. Specification (ii) employs a different measure of portfolio book-to-market equity. Specification (iii) additionally includes portfolio book equity. Table 9 presents the details of these pricing exercises.

[about here: Table 9]

The results confirm our benchmark findings in Table 3 but are associated with slightly lower measures of fit. The latter drops to 74% in specification (iii), however, the general picture remains unaffected. All models in Table 9 show that average stock returns on book-to-market and size sorted stock portfolios are related to their cash-flow sensitivities to the market's cash-flow news components in downside markets. Firms' cash-flow sensitivities to the permanent market news are not priced in any of the specifications under study.

In addition, we experimented with the real dividend growth, stock variance, and a different measure of price-earnings ratio based on the one-year moving average of past earnings (Chen and Zhao (2009)). We have also worked with inflation (Chen and Zhao, 2009) and a different measure of value spread obtained from 25 double-sort Fama-French portfolios. We conclude that our findings are largely independent of the underlying state variables in the estimation.

D.2. Other Test Assets

This subsection examines the sensitivity of our findings to the choice of test assets. The portfolios employed in our empirical tests are formed on a single-sort of firms according to firms' market values, book-to-market ratio, and past stock performance. The rationale for examining these portfolios is that size, book-to-market, and momentum based characteristics build the basis for risk factors used to explain variation in returns on other test assets. Following a similar empirical methodology, Bansal et al. (2005) show that the cross-section of these portfolio returns reflects cash-flow risks embodied in consumption growth. While differences in their cash-flow betas account for more than 60% of the variation in risk premia, our eight-beta model–depending on specification–captures about 70%-85% of these excess returns.

Table 10 gives results for three sets of VAR specifications we introduced before. Specification (i) includes excess returns, dividend yield, small-stock value spread, and short-term interest rate. Specification (ii) employs a different measure of dividend yield based on twelve-month trailing average. Specification (iii) employs a different measure of dividend yield computed as a ratio of previous period dividend to current stock price. Our findings strongly support the relative importance of firms' cash-flow characteristics relative to their discount-rate components: λ_{cc}^{+}, λ_{cc}^{-}, λ_{cd}^{+}, and λ_{cd}^{-}'s exceed in absolute values λ_{dc}^{+}, λ_{dc}^{-}, λ_{dd}^{+}, and λ_{dd}^{-}'s, respectively. The estimate of λ_{cc}^{+} is negative suggesting that strong performance in good times translates in a discount. In contrary, the coefficient λ_{cc}^{-} is highly significant and positive suggesting that weak performance in bad times commands a premium. Furthermore, firms' cash-flow sensitivities associated with downside markets command a higher compensation than in upside markets, i.e. λ_{cc}^{-} exceeds λ_{cc}^{+}, and λ_{cd}^{-} exceeds λ_{cd}^{+} in absolute values. Finally, taking into account both economic and statistical importance, risks behind $\beta_{i,cc}^{-}$'s and $\beta_{i,cd}^{-}$'s are the key to explain cross-sectional differentials on the 30 portfolio returns. The estimates of λ_{cd}^{-} are significant albeit negative as indicated by the estimates in Table 10. Campbell and Vuolteenaho (2004) and Chen and Zhao (2009) similarly report negative estimates of the discount-rate news for VAR systems based on excess return, term yield spread, value spread, and price-earnings ratio.

[about here: Table 10]

As an additional exercise, we follow Lewellen et al. (2010) and include 30 US industry portfolios[2] in test assets alongside with 25 benchmark size and book-to-market sorted portfolios in order to reduce commonalities in value and growth portfolios due to the strong factor structure. Alternatively, we have extended a cross-section of 30 single-sorted portfolios constructed on size, book-to-market and momentum with 30 industry portfolios. Finally, we have combined 25 double-sorted with 30 single-sorted stock returns. Results from these exercises are very similar to our benchmark findings and omitted for brevity. None of our conclusions were affected by the choice of test assets.

D.3. Alternative Downside Risk Specifications

To guard against the possibility that our conclusions are attributed to the specific definition of downside market risk as periods in which the market news is below zero, in this subsection we explore other plausible cutoffs. We evaluate three cases in Table 11. Specification (i) is in line with the measure of downside risk introduced by Bawa and Lindenberg (1977). For instance, $\beta_{i,cc}^{-}$ is computed as

[2] The set of industry portfolios is based on portfolio four-digit SIC code and is kindly provided in the online library of Kenneth R. French.

$$\beta_{i,cc}^{-} \equiv \frac{Cov_t(N_{c_i}, N_{c_m} \,|r_m^e \leq \overline{r_m^e})}{Var_t(N_m \,|r_m^e \leq \overline{r_m^e})}, \tag{29}$$

where $\overline{r_m^e}$ denotes the time-series mean of excess market return, and all remaining betas are computed accordingly. In specification (i) downside (upside) markets are defined as periods in which the unconditional market excess return is below (above) its mean. In specifications (ii) and (iii) we follow Ang et al. (2006) and use zero rate of return and risk-free rate as cutoff points to determine up markets and down markets.

[about here: Table 11]

Using either of these alternative cutoff points yields very similar qualitative results. As emphasized by Ang et al. (2006), downside risk premia are indeed driven by asymmetric treatment of losses and gains and not by the particular benchmark specification. Changes in the downside risk specification do not matter. Across the three specifications we consider in Table 11, λ_{cc}^{-} emerges as the only significant determinant of differences in equity premium across assets.

D.4. Direct Cash-Flow News Estimation

So far, this paper has followed a voluminous literature in macroeconomics and finance initiated by Campbell (1991) and Campbell and Ammer (1993) to estimate the discount-rate news from a VAR, while backing out the cash-flow news as a residual from an identity. Chen and Zhao (2009) discuss several limitations of this procedure. In particular, they point out that the treatment of the cash-flow component in return decompositions as a residual might unfavorably affect the discount-rate premia and overstate the importance of the cash-flow risks at the same time. Against this backdrop, Engsted et al. (2012) argue that this criticism might be misplaced on grounds of invalid VAR decompositions. In a properly specified model, the computation method plays no role and it makes not difference whether the cash-flow news or discount-rate news is backed out residually or estimated directly. Campbell et al. (2010) raise a similar argument and show that a correct return decomposition relies crucially on the choice of the state variables but is not necessarily influenced by the decision to forecast returns or cash flows.

In this subsection, we address the debate by following the suggestion of Chen and Zhao (2009) to model both news series directly using two separate VAR systems. This method acknowledges the fact that there is a noise component in returns which cannot be explained by permanent shocks to the dividend stream or transitory shocks associated with changes in discount rates:

$$N_{t+1} = \widetilde{N_{c,t+1}} - N_{d,t+1} + \varepsilon_{t+1}, \tag{30}$$

where the discount-rate news $N_{d,t+1}$ is extracted via Equation (3). The cash-flow news $\widetilde{N_{c,t+1}}$ can be further identified from a VAR whose first component is the dividend growth rate as

$$\widetilde{N_{c,t+1}} = \mathbf{e1}'\mathbf{\Lambda}_1 \widetilde{\mathbf{w}_{t+1}}, \tag{31}$$

where $\mathbf{\Lambda}_1 \equiv \rho \mathbf{A}_1 \left(\mathbf{I} - \rho \mathbf{A}_1\right)^{-1}$, $\mathbf{A}_1$ is the companion matrix and $\widetilde{\mathbf{w}_{t+1}}$ is the residual vector.

To ensure that our results do not depend on the estimation method or the choice of state variables, we estimate three alternative VAR models to model $\widetilde{N_{c,t+1}}$ directly. Table 12 summarizes our findings. The state variables are dividend growth, market excess return and dividend yield computed as the log ratio of dividends and prices in specification (i). Specification (ii) differs from (i) in that it employs a different measure of dividend yield based on the 12-month trailing average of dividends. Finally, specification (iii) differs from (ii) in that it additionally includes the short-term interest rate as a state variable. The variables are motivated by Chen and Zhao (2009) empirically due to their potential to forecast dividend growth. To mitigate the seasonality of dividends we work with annual growth rates. We obtain qualitatively similar results for price-to-earnings ratio, stock variance, inflation, and value spread.

[about here: Table 12]

We find that several beta components are strongly related to the pattern in average returns across assets. In particular, systematic risks embodied in stocks' cash-flow sensitivities to permanent aggregate shocks during market declines command a positive and highly significant premium. Most interestingly, we find substantially lower estimates of the cash-flow risk price compared with the our benchmark estimates. Chen and Zhao (2009), Botshekan et al. (2013) and Galsband and Nitschka (2013) derive a similar conclusion.

D.5. Additional Checks

To verify that our results are not attributed to the specific time period we study, we change the length of the sample. The period since 1963 has been the subject of much recent research in the finance literature, and most of the evidence on the book-to-market anomaly is obtained for the post-1963 period. Campbell and Vuolteenaho (2004) document a particularly poor performance of the CAPM in the post-1963 period. We evaluated our eight-beta model on a sample split in 1963 as well as repeated the cross-sectional pricing exercise for two sample halves before and after 1970 when the total sample is mechanically divided in the middle. In our tests, firms' cash-flow sensitivities to market-wide permanent news command a positive premium of about 20% p.a. The premium on downside cash-flow risk is estimated with a right sign and high precision in all cases. We find that the general performance of the eight-beta model is slightly lower in the post-1963 or the post-1970 periods. However, the adjusted cross-sectional R^2 measures never falls below 60%.

We did a number of additional experiments. We used other plausible linearization parameter values, controlled for residual size and book-to-market effects, and employed a relative measure of downside and upside betas (Ang et al. (2006)). We experimented with time-varying betas, and tested different window lengths for in- and out-of-sample predictive regressions. Our results support that the eight-beta model is a powerful tool to describe financial market data. Our findings highlight the importance of downside fluctuations in the slow-moving persistent component of fundamentals in understanding the risk exposure of assets.

E. Out-Of-Sample Evidence

Finally, we perform in- and out-of-sample regressions with time-varying betas estimated using overlapping rolling windows. For out-of-sample tests, we calculate the betas using rolling window as described above but employ the average of the next rolling window out-of-sample returns. For instance, the first cross-sectional regression relates the betas estimated over the 90-month window from January 1929 to June 1936 to average returns over July 1936 to December 1943. This test provides an out-of-sample evidence for predictive power of expected returns. Our exercise suggests that permanent downside risks embodied in firms' cash-flow components always command a positive and statistically significant premium. This result holds for different rolling window intervals and across different test assets. The eight-beta model explains no less than 80% of the cross-sectional variation in average stock returns. Our results are very similar for news components obtained with a broad range of alternative state variables and over different sample periods.

V. Conclusions

Financial economists have long relied on a log-linearized approximation to single-out the permanent and transitory components in excess returns. In this paper, we propose an intuitive extension to this approach which encompasses upside and downside components in market-wide and firm-level news. Empirically, our results shed light on several important issues debated in finance at least since the late 1980s.

We show that a large part of cross-sectional variation in excess stock returns in attributable to systematic risks embodied in stocks' cash-flow sensitivities to permanent aggregate shocks during market declines. At a mechanical level, this result emerges as a natural outcome from combining the Campbell et al. (2010) risk story with Botshekan et al. (2013) return explanation. At a conceptual level, we find that downside betas of value (growth) stocks with the aggregate market's cash-flow (discount-rate) shocks are determined by cash-flow fundamentals of individual growth and value firms. Systematic risks embodied in downside stocks' cash-flow sensitivities to permanent aggregate shocks require a positive and highly significant premium.

More generally, our results help to explain the common sources of comovement in stock prices. Common variation in asset prices is a key to measures of systematic risk that rational investors use to determine the value of market investment. Our evidence points to the importance of cross-sectional differences in conditional persistent components of stock fundamentals in understanding the risk-return trade-off in equity markets.

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Table 1: Summary Statistics: Portfolio Returns

The table presents average excess returns and standard deviations in percent per annum for the 25 Fama-French portfolios sorted by size (S) and book-to-market equity (B). The sample period is monthly running from January 1929 to September 2012. S1 denotes the lowest market equity quintile, S5 the highest market equity quintile, B1 the lowest book-to-market equity quintile, and B5 the highest book-to-market equity quintile.

	B1	B2	B3	B4	B5	B5-B1	B1	B2	B3	B4	B5
				Mean					Std		
S1	4.68	9.16	11.78	13.46	15.93	11.25	42.35	36.68	32.10	30.11	33.36
S2	6.55	10.81	12.07	12.40	13.76	7.21	27.90	27.38	25.63	26.55	30.49
S3	7.61	9.85	11.03	11.47	13.12	5.50	26.76	23.03	23.52	23.82	29.97
S4	7.47	8.21	9.79	10.82	12.07	4.60	21.72	21.99	22.43	24.49	31.25
S5	6.42	6.61	7.48	8.00	10.21	3.79	19.01	18.24	20.01	24.09	26.30

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), small stock value spread (vs), price-earnings ratio (pe), and the short-term interest rate (i). OLS t-statistics are in parentheses. Each row corresponds to a different dependent variable. The first six columns report coefficients on the explanatory variables listed in the column header; the last column shows the adjusted $\overline{R}^2$ statistics in percent. The correlation between the implied cash-flow and discount-rate news is -0.23.

Variable	Constant	$r^e_{M,t}$	vs_t	pe_t	i_t	$\overline{R^2}$
$r^e_{M,t+1}$	0.08	0.11	-0.01	-0.02	-0.02	2.40
	(3.97)	(3.37)	(-2.44)	(-3.45)	(-1.99)	
vs_{t+1}	0.02	-0.01	0.99	-0.00	-0.00	98.14
	(1.25)	(-0.20)	(190.34)	(-0.30)	(-0.53)	
pe_{t+1}	0.02	0.51	-0.00	0.99	0.00	99.01
	(1.80)	(24.46)	(-0.51)	(296.53)	(0.28)	
i_{t+1}	0.02	-0.04	-0.01	0.00	0.97	95.13
	(0.82)	(-1.32)	(-1.70)	(0.58)	(121.57)	

Table 3: (Intertemporal) Capital Asset Pricing Model

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 25 size- and book-to-market sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. The estimated models are (i) the standard CAPM, (ii) the two-beta ICAPM with cash-flow and discount-rate risks, (iii) the four-beta ICAPM with market and firm-level cash-flow and discount-rate risks, (iv) the four-beta ICAPM with upside and downside cash-flow and discount rate risks, and (v) the eight-beta ICAPM with upside and downside market-wide and firm-level cash-flow and discount-rate risks. The market-wide cash-flow and discount-rate news terms are extracted using the VAR of Table 2. Portfolio-specific cash-flow and discount-rate news terms are constructed from a VAR system with firm-level characteristics including excess return, book-to-market equity, and average size for each portfolio separately. The downside (upside) markets are defined as periods in which the unexpected market excess return is below (above) its mean. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)		(iv)		(v)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	3.94	(0.65)	3.54	(0.68)	7.58	(7.81)	10.94	(2.12)	7.29	(16.00)
λ_m	5.09	(1.02)								
λ_c			34.56	(2.30)						
λ_d			-2.07	(-0.37)						
λ_{cc}					27.31	(1.95)				
λ_{cd}					-1.18	(-0.23)				
λ_{dc}					124.39	(3.60)				
λ_{dd}					-80.62	(-1.28)				
λ_c^+							-4.08	(-0.52)		
λ_c^-							40.58	(1.96)		
λ_d^+							2.97	(0.49)		
λ_d^-							-17.88	(-1.72)		
λ_{cc}^+									-6.95	(-1.26)
λ_{cc}^-									33.53	(3.92)
λ_{cd}^+									-0.73	(-0.12)
λ_{cd}^-									-11.43	(-2.29)
λ_{dc}^+									17.56	(1.01)
λ_{dc}^-									34.98	(1.76)
λ_{dd}^+									-7.30	(-0.50)
λ_{dd}^-									-76.06	(-5.06)
$\overline{R}^2$	4.28		27.58		55.59		56.49		89.39	
$MSPE$	6.75		4.89		2.72		2.67		0.48	
$MAPE$	2.09		1.63		1.42		1.25		0.52	

Table 4: Pricing Errors

The table reports the pricing errors in percent per annum of each of 25 size- (S) and book-to-market- (B) sorted portfolios from the Fama-MacBeth (1973) regressions presented in Table 3. S1 refers to the portfolios with the smallest firms, and S5 includes the portfolios with largest firms. Similarly, B1 refers to the portfolios with lowest book-to-market ratios, and B5 includes the portfolios with the highest book-to-market ratios. The estimated models are (i) the standard CAPM, (ii) the two-beta ICAPM by Campbell and Vuolteenaho (2004), (iii) the four-beta ICAPM by Campbell et al. (2010), (iv) the four-beta ICAPM by Botshekan et al. (2013), and (v) the eight-beta ICAPM.

	(i)	(ii)	(iii)	(iv)	(v)
S1B1	-7.35	-6.73	-3.51	-2.62	-0.44
S1B2	-1.90	0.43	1.73	-3.12	-0.29
S1B3	0.97	1.39	1.22	-0.33	-0.63
S1B4	3.12	3.34	0.14	2.57	-0.22
S1B5	5.19	4.73	2.04	4.22	0.57
S2B1	-3.67	-0.78	-0.77	0.79	0.18
S2B2	0.57	1.71	2.19	0.90	1.66
S2B3	2.26	2.38	2.25	1.28	0.61
S2B4	2.37	1.97	1.12	1.01	-0.09
S2B5	3.07	1.92	0.54	1.86	0.61
S3B1	-2.68	-0.38	-1.28	0.85	-0.31
S3B2	0.23	0.52	0.94	-0.48	-0.34
S3B3	1.35	0.74	1.75	-0.10	0.19
S3B4	1.88	0.92	1.07	-0.67	-0.15
S3B5	2.32	0.36	2.36	0.18	0.90
S4B1	-1.91	-0.28	-0.93	1.29	-0.01
S4B2	-1.24	-1.01	-1.10	-1.30	-2.09
S4B3	0.32	-0.13	-1.87	-1.33	0.23
S4B4	1.01	-0.44	0.16	-0.79	-0.63
S4B5	1.01	-1.43	-1.74	0.05	0.25
S5B1	-2.40	-1.25	-0.24	0.26	0.48
S5B2	-2.01	-1.48	0.24	-0.66	0.71
S5B3	-1.38	-2.06	-1.43	-1.29	0.07
S5B4	-1.58	-3.02	-2.20	-2.92	-0.57
S5B5	0.46	-1.45	-2.69	0.36	-0.68

Table 5: Portfolio Risk Measures

The table reports the average betas of 25 size- (S) and book-to-market (B) portfolios corresponding to equity premium components presented in Table 6. The betas are computed as time-series averages of betas over the 90-month rolling window. S1 denotes the lowest market equity quintile, S5 the highest market equity quintile, B1 the lowest book-to-market equity quintile, and B5 the highest book-to-market equity quintile. The market-wide cash-flow and discount-rate news terms are extracted using the VAR of Table 2. Portfolio-specific cash-flow and discount-rate news terms are constructed from a VAR system with firm-level characteristics including excess return, book-to-market equity, and average size for each portfolio separately.

	B1	B2	B3	B4	B5	B5-B1	B1	B2	B3	B4	B5	B5-B1
			β_{cc}^{+}						β_{cc}^{-}			
S1	-0.38	-0.20	-0.15	-0.13	0.01	0.39	0.07	0.13	0.08	0.05	0.09	0.02
S2	-0.29	-0.18	-0.03	-0.01	0.05	0.35	0.03	0.03	0.05	0.10	0.13	0.10
S3	-0.35	-0.05	0.04	0.10	0.30	0.66	-0.01	0.07	0.08	0.10	0.21	0.22
S4	-0.15	0.03	0.04	0.19	0.29	0.45	-0.01	0.07	0.06	0.07	0.12	0.13
S5	-0.08	0.04	0.13	0.28	0.22	0.30	-0.07	0.00	-0.04	0.05	0.09	0.15
			β_{cd}^{+}						β_{cd}^{-}			
S1	0.57	0.28	0.20	0.20	0.03	-0.55	0.48	0.20	0.13	0.03	0.11	-0.38
S2	0.43	0.24	0.00	0.02	0.06	-0.37	0.32	0.14	0.04	0.00	0.07	-0.25
S3	0.50	0.09	-0.09	-0.10	-0.22	-0.71	0.26	0.06	0.01	-0.11	0.03	-0.24
S4	0.31	0.02	0.06	-0.15	-0.08	-0.39	0.17	0.01	-0.07	-0.08	0.01	-0.16
S5	0.10	-0.13	-0.17	-0.22	-0.17	-0.27	0.03	-0.06	-0.15	-0.20	-0.06	-0.09
			β_{dc}^{+}						β_{dc}^{-}			
S1	0.02	-0.05	0.01	0.07	0.07	0.04	0.01	0.00	0.02	0.06	0.05	0.04
S2	-0.00	-0.01	-0.02	0.01	0.09	0.09	0.00	0.02	0.00	0.02	0.03	0.03
S3	-0.01	-0.02	-0.02	0.02	-0.07	-0.06	0.01	0.01	-0.01	0.00	-0.04	-0.05
S4	0.01	-0.02	0.09	-0.02	0.05	0.03	-0.01	-0.00	0.02	-0.00	0.02	0.03
S5	0.01	-0.00	0.01	-0.02	0.06	0.06	0.00	-0.01	0.03	0.01	0.03	0.03
			β_{dd}^{+}						β_{dd}^{-}			
S1	-0.01	0.05	-0.02	-0.15	-0.11	-0.10	0.03	0.01	0.01	0.01	0.01	-0.02
S2	0.02	-0.01	0.00	-0.05	-0.15	-0.17	0.01	0.01	-0.00	0.01	0.02	0.01
S3	0.00	0.00	0.02	-0.04	0.09	0.09	0.01	0.00	-0.00	0.01	-0.01	-0.02
S4	-0.03	0.01	-0.20	0.01	-0.10	-0.06	-0.02	-0.00	0.05	0.00	0.02	0.04
S5	0.00	0.05	-0.05	-0.04	-0.09	-0.09	-0.01	0.01	0.01	0.03	-0.01	-0.00

Table 6: Equity Premium Contributions

The table reports the time-series averages of equity premium components in percent per annum and their t-statistics. The estimates are computed as time-series averages of $\lambda^{\cdot}_{jt} \cdot \overline{\beta_{jt}}$ where $\overline{\beta_{jt}}$ is the cross-sectional mean of beta of risk factor j over the 90-month rolling window t, and $\lambda^{\cdot}_{jt}$ is the estimated risk premium for risk factor j from monthly recursive cross-sectional regressions of average returns over the 90-month rolling window t on a constant and betas over the same rolling window. Specification (i) includes all 25 size- and book-to-market portfolios, specification (ii) includes 5 value portfolios with highest book-to-market ratios, and specification (iii) includes 5 growth portfolios with lowest book-to-market ratios.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
$\lambda^{+}_{cc}\beta^{+}_{cc}$	0.56	(13.58)	1.27	(13.67)	0.29	(2.97)
$\lambda^{-}_{cc}\beta^{-}_{cc}$	0.61	(14.20)	0.95	(11.94)	-0.11	(-1.50)
$\lambda^{+}_{cd}\beta^{+}_{cd}$	0.19	(2.78)	0.36	(3.31)	-0.05	(-0.40)
$\lambda^{-}_{cd}\beta^{-}_{cd}$	0.41	(5.84)	1.20	(11.75)	-0.67	(-5.89)
$\lambda^{+}_{dc}\beta^{+}_{dc}$	0.15	(2.55)	0.08	(1.00)	0.12	(1.90)
$\lambda^{-}_{dc}\beta^{-}_{dc}$	0.05	(1.79)	0.23	(4.02)	-0.17	(-4.96)
$\lambda^{+}_{dd}\beta^{+}_{dd}$	0.02	(0.63)	0.21	(4.27)	-0.10	(-2.46)
$\lambda^{-}_{dd}\beta^{-}_{dd}$	0.16	(2.36)	0.58	(5.19)	-0.20	(-3.10)

Table 7: Dividend Yield as a State Variable

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 25 size- and book-to-market sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. The market-wide cash-flow and discount-rate news components are extracted from three sets of state variables. Specification (i) includes excess return, dividend yield, small-stock value spread, and short-term interest rate. Specification (ii) employs a different measure of dividend yield based on twelve-month trailing average. Specification (iii) employs a different measure of dividend yield computed as a ratio of previous period dividend to current stock price. Portfolio-specific cash-flow and discount-rate news terms are constructed from a VAR system with firm-level characteristics including excess return, book-to-market equity, and average size for each portfolio separately. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	7.30	(14.29)	7.34	(14.34)	7.62	(17.14)
λ_{cc}^+	-2.48	(-0.42)	-3.53	(-0.58)	-5.86	(-1.04)
λ_{cc}^-	19.49	(2.46)	18.36	(2.34)	20.96	(2.91)
λ_{cd}^+	4.91	(0.60)	3.71	(0.48)	2.66	(0.37)
λ_{cd}^-	-32.39	(-3.47)	-27.02	(-3.22)	-28.12	(-3.53)
λ_{dc}^+	18.59	(0.96)	9.00	(0.42)	5.28	(0.27)
λ_{dc}^-	1.38	(0.80)	9.12	(0.48)	7.44	(0.44)
λ_{dd}^+	-12.86	(-0.70)	-17.24	(-0.90)	-16.62	(-1.00)
λ_{dd}^-	-83.34	(-3.72)	-97.85	(-3.90)	-102.07	(-4.58)
$\overline{R}^2$	87.68		87.49		90.03	
$MSPE$	0.60		0.61		0.49	
$MAPE$	0.56		0.58		0.50	

Table 8: Common Set of State Variables

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 25 size- and book-to-market sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. The market-wide and portfolio-specific cash-flow and discount-rate news components are extracted from three sets of state variables specified in Table 7. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	2.50	(0.60)	4.29	(1.06)	3.49	(0.87)
λ_{cc}^{+}	-5.09	(-0.66)	-7.11	(-1.04)	-5.60	(-0.74)
λ_{cc}^{-}	25.90	(2.29)	25.72	(2.37)	25.35	(2.29)
λ_{cd}^{+}	3.53	(0.39)	2.98	(0.39)	3.71	(0.43)
λ_{cd}^{-}	-17.88	(-1.30)	-16.23	(-1.39)	-19.01	(-1.46)
λ_{dc}^{+}	95.82	(3.32)	76.91	(2.93)	84.78	(3.02)
λ_{dc}^{-}	-90.17	(-2.57)	-71.39	(-2.31)	-79.99	(-2.34)
λ_{dd}^{+}	28.54	(1.38)	20.69	(1.05)	24.10	(1.12)
λ_{dd}^{-}	-23.90	(-0.84)	-19.25	(-0.76)	-23.54	(-0.82)
$\overline{R}^2$	81.90		84.16		82.67	
$MSPE$	0.89		0.78		0.85	
$MAPE$	0.74		0.70		0.72	

Table 9: Alternative Firm-Level States Variables

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 25 size- and book-to-market sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. Market-wide news is obtained from a VAR system summarized in Table 2. For computation of firm-level news, the VAR system relies on three sets of state variables. Specification (i) includes excess portfolio return, portfolio book-to-market equity, and average firm size. Specification (ii) employs a different measure of portfolio book-to-market equity. Specification (iii) additionally includes portfolio book equity. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	7.29	(16.00)	7.54	(11.14)	6.87	(8.30)
λ_{cc}^{+}	-6.95	(-1.26)	-8.95	(-0.99)	-11.03	(-1.13)
λ_{cc}^{-}	33.53	(3.92)	39.73	(2.96)	34.76	(2.17)
λ_{cd}^{+}	-0.73	(-0.12)	0.09	(0.01)	3.02	(0.40)
λ_{cd}^{-}	-11.43	(-2.29)	-12.35	(-2.32)	-12.72	(-2.03)
λ_{dc}^{+}	17.56	(1.01)	23.76	(0.61)	-28.24	(-0.77)
λ_{dc}^{-}	34.98	(1.76)	25.87	(0.78)	-11.96	(-0.45)
λ_{dd}^{+}	-7.30	(-0.50)	-23.04	(-0.91)	-52.39	(-2.56)
λ_{dd}^{-}	-76.06	(-5.06)	-88.00	(-2.99)	-45.64	(-1.70)
$\overline{R}^2$	89.39		79.51		73.86	
$MSPE$	0.48		1.01		1.28	
$MAPE$	0.52		0.81		0.91	

Table 10: 30 Single-Sorted Portfolios

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 10 size-, 10 book-to-market- and 10 momentum-sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. The underlying VAR specifications to extract the cash-flow and discount-rate news are defined in Table 7. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	14.53	(2.54)	18.03	(4.51)	14.93	(3.05)
λ_{cc}^{+}	-34.28	(-2.62)	-33.86	(-4.27)	-32.97	(-3.28)
λ_{cc}^{-}	51.57	(3.59)	48.70	(4.89)	48.50	(4.13)
λ_{cd}^{+}	15.35	(1.38)	12.53	(2.04)	16.17	(1.75)
λ_{cd}^{-}	-54.85	(-3.20)	-52.02	(-5.00)	-54.13	(-3.77)
λ_{dc}^{+}	-31.72	(-1.22)	-24.04	(-1.37)	-28.78	(-1.29)
λ_{dc}^{-}	42.30	(1.37)	28.26	(1.31)	33.78	(1.26)
λ_{dd}^{+}	-58.91	(-1.52)	-52.12	(-2.54)	-65.56	(-2.01)
λ_{dd}^{-}	43.91	(0.78)	30.87	(1.12)	51.58	(1.13)
$\overline{R}^2$	69.49		86.31		81.65	
$MSPE$	1.70		0.76		1.28	
$MAPE$	1.02		0.66		0.89	

Table 11: Alternative Downside Risk Specifications

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 25 size- and book-to-market sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. Specification (i) defines downside (upside) markets as periods in which the unconditional market excess return is below (above) its mean. Specification (ii) defines downside (upside) markets as periods in which unconditional market excess return is below (above) zero. Specification (iii) defines downside (upside) markets as periods in which the unconditional market excess return is below (above) the risk-free rate. The design of news follows otherwise the benchmark case in Table 3. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	7.33	(16.88)	7.48	(16.13)	7.35	(8.29)
λ_{cc}^{+}	-6.94	(-1.33)	-7.44	(-1.14)	0.07	(0.28)
λ_{cc}^{-}	36.61	(4.34)	32.09	(3.81)	41.42	(2.83)
λ_{cd}^{+}	0.61	(0.11)	-0.17	(-0.03)	0.10	(0.41)
λ_{cd}^{-}	-14.86	(-3.16)	-12.10	(-2.40)	-1.68	(-0.31)
λ_{dc}^{+}	28.48	(2.00)	34.73	(2.12)	-0.31	(-0.22)
λ_{dc}^{-}	24.32	(1.37)	10.33	(0.58)	108.58	(3.13)
λ_{dd}^{+}	-0.58	(-0.05)	-1.85	(-0.13)	-0.23	(-0.14)
λ_{dd}^{-}	-75.31	(-5.26)	-73.66	(-5.25)	-63.93	(-1.08)
$\overline{R}^2$	91.05		89.60		64.25	
$MSPE$	0.44		0.51		1.75	
$MAPE$	0.49		0.53		1.11	

Table 12: Direct Estimation of Cash-Flow News

The table reports Fama-MacBeth (1973) risk prices in percent per annum using 25 size- and book-to-market sorted portfolios. Shanken (1992) corrected t-statistics are presented in the adjacent column. The market-wide discount-rate news is extracted using the VAR of Table 2. The market-wide cash-flow news is estimated in a separate VAR system. Specification (i) employs dividend growth, market excess return and dividend yield as state variables. Specification (ii) employs dividend growth, market excess return and the 12-month trailing average of the dividend yield as state variables. Specification (iii) employs dividend growth, market excess return, the 12-month trailing average of the dividend yield, and the short-term interest rate as state variables. The R^2 (in percent) are corrected for degrees of freedom. Mean squared pricing error ($MSPE$) and mean absolute pricing error ($MAPE$) are in percent per annum.

	(i)		(ii)		(iii)	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
λ_0	7.60	(16.53)	7.75	(16.84)	7.68	(14.82)
λ_{cc}^+	1.66	(5.27)	1.46	(4.99)	1.41	(4.57)
λ_{cc}^-	2.46	(4.39)	2.42	(4.20)	1.84	(3.63)
λ_{cd}^+	-24.94	(-3.78)	-23.82	(-3.61)	-23.45	(-3.41)
λ_{cd}^-	-10.37	(-1.83)	-10.52	(-1.89)	-4.68	(-0.93)
λ_{dc}^+	4.41	(3.10)	3.50	(2.45)	0.64	(0.45)
λ_{dc}^-	1.36	(0.92)	1.62	(0.96)	2.49	(1.76)
λ_{dd}^+	-42.82	(-5.00)	-39.29	(-4.56)	-37.37	(-4.03)
λ_{dd}^-	-55.65	(-3.14)	-62.55	(-3.43)	-57.90	(-3.48)
$\overline{R}^2$	90.90		90.73		85.63	
$MSPE$	0.45		0.46		0.53	
$MAPE$	0.56		0.58		0.62	