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Cash Flow and Discount Rate Risk in Up and Down Markets: What Is Actually Priced?*

Mahmoud Botshekan[1], Roman Kraeussl[2], and Andre Lucas[3]

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Abstract:
We test whether asymmetric preferences for losses versus gains as in Ang, Chen, and Xing (2006) also affect the pricing of cash flow versus discount rate news as in Campbell and Vuolteenaho (2004). We construct a new four-fold beta decomposition, distinguishing cash flow and discount rate betas in up and down markets. Using CRSP data over 1963–2008, we find that the downside cash flow beta and downside discount rate beta carry the largest premia. We subject our result to an extensive number of robustness checks. Overall, downside cash flow risk is priced most consistently across different samples, periods, and return decomposition methods, and is the only component of β that has significant out-of-sample predictive ability. The downside cash flow risk premium is mainly attributable to small stocks. The risk premium for large stocks appears much more driven by a compensation for symmetric, cash flow related risk. Finally, we multiply our premia estimates by average betas to compute the contribution of the different risk components to realized average returns. We find that up and down discount rate components dominate the contribution to average returns of downside cash flow risk.

JEL Classification: G11, G12, G14

Keywords: Asset Pricing, Beta, Downside Risk, Upside Risk, Cash Flow Risk, Discount Rate Risk.

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1 Introduction

The CAPM model of Sharpe (1964) and Lintner (1965) has since long been the most well-used[1] work horse model to understand the origins of expected returns. An important further contribution of the (in)ability of the CAPM to price the cross-section of stock returns was made by Campbell and Vuolteenaho (2004). Using a return decomposition method originally proposed by Campbell and Shiller (1988) and Campbell (1991), they show that the beta of the basic CAPM can be disentangled into a discount rate and a cash flow risk related component. They argue that in an economy with many long-term investors, cash flow risk should carry a larger premium than discount rate risk. For long-term investors the negative impact of surprise discount rate increases on current realized returns is partially compensated by higher future expected returns. Using this two-fold beta decomposition, they can partially explain cross-sectional phenomena such as the origins of the size and book-to-market effects in stock returns. For instance, growth stocks typically have high betas for the market portfolio, but these betas are related to discount rates and therefore bear a lower premium. By contrast, the betas for value stocks mainly relate to cash flow risk and therefore bear a larger compensation, resulting in higher average returns.

In the current paper, we further increase the ability of the extended CAPM to increase our understanding of cross-sectional pricing determinants by proposing a four-beta decomposition. The motivation for this extension, lies in the literature on asymmetric preferences. Following the seminal work of Kahneman and Tversky (1979), there has been a large number of papers demonstrating that typical decision makers are loss averse: the negative experience of a loss looms about twice as large as the positive experience of a similarly sized gain. The notion that preferences to losses versus gains may be different has a long history in finance as well. Already Markowitz (1959) suggested to replace the variance as a (symmetric) risk measure of returns by the asymmetric semi-variance. The idea was further extended to lower partial moments and set in an equilibrium context, see for example Hogan and Warren (1974), Bawa and Lindenberg (1977), and Harlow and Rao (1989). Empirically, the importance of downside risk is supported by Ang, Chen, and Xing (2006). By conditioning a stock's covariation with the market on up

[1] The CAPM has of course seen numerous extensions, such as additional pricing factors like size, value, and momentum (Fama and French (1993), Fama and French (1996), Jegadeesh and Titman (1993), and Carhart (1997)); liquidity (Amihud (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005)); preference-based factors such as the downside betas of Ang, Chen, and Xing (2006) and the co-skewness of Friend and Westerfield (1980) and Harvey and Siddique (2000); and factors relating to deviations from market equilibria, see Lettau and Ludvigson (2001).

and down markets, they are able to define up and down betas. Using standard asset pricing methodology, they find that equity risk premia correlate with downside betas, but not as much with upside betas. Their findings suggest that investors care more about the downside risk properties of stocks than about their general covariance properties.

A very similar line of reasoning applies to the good and bad beta model of Campbell and Vuolteenaho (2004). If the market goes down, loss averse investors experience a disproportially large increase in marginal utility due to their asymmetric, kinked utility function. As a result, the impact (and trade-off) of cash flow versus discount rate shocks may become different in bull and bear markets. Combining the results of Ang et al. (2006) with those of Campbell and Vuolteenaho (2004), we expect the largest premium for downside cash flow risk. To test this conjectjure, we define a four-beta model, where we measure a stock return's covariation with cash flow and discount rate news separately in up and down markets.

Using this new four-beta decomposition and U.S. stock returns over the period 1963–2008, we investigate how the four components of beta are priced in the cross-section of stocks. We use Fama and MacBeth (1973) regressions with time varying betas to obtain risk premia estimates based on the individual stocks as test assets as in Ang, Liu, and Schwarz (2008). We find that both downside cash flow risk and downside discount rate risk are significantly priced and typically carry the largest premia. The upside pricing factors are less in magnitude and less robust. In particular, the downside cash flow risk is most consistently priced over different subperiods in our sample. The magnitude, statistical signifance, and even the sign of the other components is much more sensitive to the period used.

Interestingly, we find a strong relation between company size and downside cash flow risk. For small stocks, we obtain the largest estimated premia for the downside risk components. By contrast, moving to larger companies, the priced components of risk become more symmetric (both up and down) and are cash flow related. Such a pattern can only be established in the proposed four-beta decomposition and suggests that investors may take a different attitude towards risk compensation for small versus large stocks. If we control for book-to-market rather than for size, no such pattern can be found. Both growth and value companies in our sample produce significant prices for all four risk components, with the premia related to downside risk dominating the upside risk premia.

A crucial step in our whole analysis is the direct construction of discount rate news via a vector autoregression (VAR) model for returns. The constructed discount rate news factor is combined with the returns to back out the cash flow news factor. Chen and Zhao (2009) criticize this decomposition approach and argue that it can be highly sensitive to the variables used in the VAR model. In particular, it matters whether discount rate news is modeled (via expected returns) and cash flow news is backed out, or whether one goes the other way around. Campbell, Polk, and Vuolteenaho (2010), Chen (2010), and Engsted, Pedersen, and Tanggaard (2010) argue that the sensitivity to the decomposition sequence can be reduced considerably by including the dividend yield as one of the state variables in the VAR model. We therefore follow their approach by including dividend yield as a state variable in our VAR model as well. Still, to account for the criticism as voiced in Chen and Zhao (2009), we also test explicitly whether our results are robust to the decomposition method used. We do so by constructing direct measures of cash flow news. We confirm that the decomposition method to some extent affects the size of premia estimates. However, we still find that the downside cash flow and downside discount rate component carry the largest compensation, thus confirming our earlier results.

Estimated risk premia are only one component of required returns. To get from risk premia to required returns, each premium needs to be multiplied by its appropriate beta. To obtain insight into the economic impact of the different risk components on average returns, we therefore also have to investigate the significance of the time varying risk premia estimates times their time varying betas. In contrast to the results for the premia alone, we find that the discount rate related components of expected returns dominate in size if we correct for beta. This implies that though investors charge a higher price for downside cash flow risk exposure, the sensitivity of the average stock to this risk factor is smaller than the sensitivity to discount rate news. The impact of the downside risk components, however, remains consistently statistically significant and positive.

As a final test of our model, we investigate whether our betas also have predictive power for expected returns. We see that if we forcast 1-month out-of-sample returns, significance is lost. Monthly returns, however, are very noisy proxies for expected returns, Using 5-year out-of-sample returns instead, the results again become very clear. Downside cash flow risk is the only beta component that has a statistically significant price. The price of 4.5% per annum is smaller than for the in-sample results (6% per annum), but surprisingly close.

There are several studies that tried to develop asset pricing models based on the return decomposition approach of Campbell and Vuolteenaho (2004) to explain cross-sectional differences in average returns, see for example, Chen and Zhao (2010), Da and Warachka (2009), Koubouros, Malliaropulos, and Panopoulou (2007), Koubouros, Malliaropulos, and Panopoulou (2010), and Maio (2009). To the best of our knowledge, however, no one has tried to disentangle the pricing properties of cash flow and discount rate news in down and up markets. The closest in this respect is the recent work by Campbell, Giglio, and Polk (2010). These authors estimate the different magnitudes of discount rate and cash flow news in two particularly bad market settings: the burst of the tech bubble and stock market downturn of 2000-2001, and the financial cricis of 2007-2008. They conclude that the 2000-2001 crisis is mainly driven by bad cash flow news, whereas the more recent financial crisis has a large bad discount rate news component to it. In contrast to Campbell, Giglio, and Polk (2010), our paper does not study the composition over time of the news factors themselves, but rather focuses on the different pricing properties of discount rate and cash flow news in different market settings and over a longer period of time.

The remainder of this paper is organized as follows. Section 2 provides the background to our four-beta decomposition model and introduces the methodology used for the empirical tests. Section 3 describes the data. Section 4 discusses the empirical results and robustness checks. Section 5 concludes.

2 Methodology

2.1 Downside and Upside Betas

Following the seminal work of Kahneman and Tversky (1979), there is sufficient empirical evidence supporting the view that typical investors are loss averse, i.e., their disutility of a large loss is higher than the positive utility of a similarly sized gain. Asymmetric preferences were already used in the early finance literature to provide alternatives to the standard CAPM, which is based on the symmetric concept of variance. Markowitz (1959), for example, introduced the notion of semi-variance as a measure of risk. The notion was exploited and extended in asset pricing theory by Hogan and Warren (1974), Bawa and Lindenberg (1977), and Harlow and Rao (1989).

Harlow and Rao (1989) use the expected market return to distinguish between up and down markets. Their equilibrium framework gives rise to a downside beta, defined as

$$\beta_{i,D} = \frac{\mathrm{E}\left[(R_{it} - \mu_i)(R_{mt} - \mu_m) \middle| R_{mt} < \mu_m\right]}{\mathrm{E}\left[(R_{mt} - \mu_m)^2 \middle| R_{mt} < \mu_m\right]}, \tag{1}$$

where R_i and R_m are the return on stock i and on the market portfolio, respectively, with expectations μ_i and μ_m, respectively. Analogously, the upside beta can be defined as

$$\beta_{i,U} = \frac{\mathrm{E}\left[(R_{it} - \mu_i)(R_{mt} - \mu_m) \middle| R_{mt} \geq \mu_m\right]}{\mathrm{E}\left[(R_{mt} - \mu_m)^2 \middle| R_{mt} \geq \mu_m\right]}. \tag{2}$$

Ang et al. (2006) show that the cross-section of stock returns reflects a downside risk premium of approximately 6% p.a. They investigate whether the upside beta, downside beta, or both have a premium in the cross-section and find that risk premia mainly reflect a stock's downside and not its upside beta. They rationalize their findings by appealing to an economy with loss-averse agents. Such agents assign greater weight to the downside movements of the market than to upside movements. In this way, Ang et al. (2006) argue that downside risk is a separate risk attribute from other well-known risk premium determinants such as size, book-to-market, momentum, and liquidity.

2.2 Cash Flow and Discount Rate Betas

Campbell and Vuolteenaho (2004) take a different perspective and decompose the market return into two components related to cash flow and discount rate risk, respectively. Using these two components, the beta of a stock can be decomposed analogously. Part of beta is due to covariation of the individual stock's return with the market's discount rate news factor. This is the so-called discount rate beta. The other part is due to covariation with the market's cash flow factor and is called the cash flow beta. Campbell and Vuolteenaho label the discount rate beta as a 'good', and the cash flow beta as a 'bad' beta. Their terminology stems from the fact that discount rate news has two off-setting effects. If discount rates increase unexpectedly, current prices decrease and realized returns are negative. For long-term investors, however, these wealth decreases are partially off-set by increases in expected future returns, as the investment opportunity set has improved.

Campbell and Vuolteenaho argue that the presence of many long-term investors in the market causes a higher premium for assets that co-vary more with the market's cash flow news than with the discount rate factor. They also show that different loadings to cash flow and discount rate news explain part of the size and value premia puzzles. The main reason is that while growth stocks (which have low average returns) have high betas for the market portfolio, these betas are predominantly 'good' betas with low risk premia. Value stocks, by contrast, have high average returns, but also higher 'bad' betas than growth stocks. Similarly, small stocks have considerably higher cash flow betas than large stocks, which is in line with the higher average realized returns for these stocks.

Our approach to decompose market returns in their discount rate and cash flow components is similar to Campbell and Vuolteenaho (2004) and uses the return decomposition technique of Campbell and Shiller (1988) and Campbell (1991). Campbell and Shiller (1988) use a loglinear approximation of the present value relation for stock prices that allows for time-varying discount rates. They obtain the following return decomposition

$$\begin{aligned} r_{m,t+1} - \mathrm{E}_t r_{m,t+1} &\approx (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{i=0}^{\infty} \rho^i \Delta d_{t+1+i} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{m,t+1+j} \\ &\equiv N_{CF,t+1} - N_{DR,t+1}, \end{aligned} \tag{3}$$

where r_{mt} is the log market return at time t, d_t is the log dividend paid by the stock at time t, Δ denotes the first difference operator, E_t denotes the rational expectations operator given the information set available at time t, and ρ is a linearization parameter defined as $\rho \equiv 1/(1 + \exp(\overline{dp}))$, where $\overline{dp}$ is the average log dividend price ratio. We follow Campbell and Vuolteenaho (2004)and assume an annual value of $\rho = 0.95$. The factor $N_{CF,t+1}$ denotes news about future cash flows, i.e., the change in the discounted sum of current and future expected dividend growth rates. Similarly, $N_{DR,t+1}$ denotes news about future discount rates, i.e., the change in the discounted sum of future expected returns.

Following the decomposition of the market return into two separate news factors, two separate betas can be defined. The cash flow beta is given as

$$\beta_{i,CF} = \frac{\mathrm{cov}(R_{i,t}, N_{CF,t})}{\mathrm{var}(u_{mt})}, \tag{4}$$

and the discount rate beta as

$$\beta_{i,DR} = \frac{\mathrm{cov}(R_{i,t}, -N_{DR,t})}{\mathrm{var}(u_{mt})}, \tag{5}$$

where $u_{mt} = r_{mt} - \mathrm{E}_{t-1} r_{mt} = N_{CF,t} - N_{DR,t}$ is the unexpected market return at time t.

The key step in operationalizing (3) and calculating (4) and (5) is to postulate a model for expected future returns $\mathrm{E}_t[r_{t+j}]$ for $j = 0, 1, \ldots$ We follow the standard approach as in Campbell and Vuolteenaho (2004) and assume the data is generated by a vector autoregression (VAR). In the VAR model the discount rate and cash flow news can be backed out directly from the VAR residuals.

The VAR model is given by

$$z_{t+1} = a + \Gamma z_t + u_{t+1}, \tag{6}$$

$$r_{m,t+1} = e_1' z_{t+1}, \tag{7}$$

where z_{t+1} is a $k \times 1$ state vector with $r_{m,t+1}$ as its first element, a is a $k \times 1$ vector of constants, Γ is an $k \times k$ matrix of coefficients, e_1 is the first column from the $k \times k$ unit matrix I_k, and u_{t+1} is a vector of serially independent random shocks. The first element of u_{t+1} thus equals the unexpected market return at time $t+1$, $e_1' u_{t+1} = u_{m,t+1}$. By recursively substituting (6) in (3), we obtain the cash flow and discount rate factors as

$$N_{DR,t+1} = e_1' \Lambda u_{t+1}, \quad and \quad N_{CF,t+1} = e_1' (\mathrm{I}_k + \Lambda) u_{t+1}, \tag{8}$$

with $\Lambda = \rho\Gamma(\mathrm{I}_k - \rho\Gamma)^{-1}$.

The VAR approach is the dominant method in the return decomposition literature. Chen and Zhao (2009) argue that the results based on the VAR methodology are sensitive to the decision to forecast expected returns explicitly while treating cash flow components as residuals, as in (8). Campbell, Polk, and Vuolteenaho (2010), however, argue that when the VAR contains the dividend-price ratio as a state variable, there is little difference between (i) an approach that backs out the cash flow news component from a directly modeled discount rate news component, and (ii) an approach that backs out the discount rate news component from a modeled cash flow component. As also pointed out by Chen (2010), the reason is that return, dividend growth, and dividend yield are related by an (linearized) accounting identity, such that one can use each combination of two variables to back out the third. Chen therefore recommends that dividend yield should always be included in the VAR state variables. The findings are confirmed by Engsted, Pedersen, and Tanggaard (2010). They also show that in order for the decomposition to be independent of which news component is treated as a residual, the underlying VAR model has to include the dividend-price ratio. Also the additional state variables have to be common to the computation of either return news or dividend news.

Based on the above arguments, we also include the dividend yield in our VAR model. However, to still check the robustness of our results to the decomposition method used, we also provide results in Section 4 based on alternative methods of return decomposition that uses direct cash flow modeling.

2.3 The Four-Beta Model

The decomposition of Campbell and Vuolteenaho (2004) does not make a distinction between upside and downside risk. The arguments based on asymmetric preferences by investors are, however, equally applicable in a context where we disentangle cash flow and discount rate risk. In particular, given the pricing results in Ang et al. (2006) as well as Campbell and Vuolteenaho (2004), it is unclear whether downside risk is priced higher than upside risk, cash flow risk is priced higher than discount risk, or any combination of these. In particular, we would like to test for the price of downside risk, cash flow risk, and discount rate risk while controlling for the other types of risk. In order to do this, we propose a new four-fold beta model. The aim of this model is to isolate the relative importance of the cash flow and discount rate news component in up and down markets. This allows us to better pinpoint the origin of risk premia in the cross-section of stock returns. The new model distinguishes four different betas: a downside cash flow beta, a downside discount rate beta, an upside cash flow beta, and an upside discount rate beta. Following the earlier definitions, the betas are defined as

$$\beta_{i,DCF} = \mathrm{E}\left[(R_{it}-\mu_i)N_{CF,t}\middle|\, u_{mt}<0\right] \;/\; \mathrm{E}\left[u_{mt}^2\middle|\, u_{mt}<0\right], \tag{9}$$

$$\beta_{i,DDR} = -\mathrm{E}\left[(R_{it}-\mu_i)N_{DR,t}\middle|\, u_{mt}<0\right] \;/\; \mathrm{E}\left[u_{mt}^2\middle|\, u_{mt}<0\right], \tag{10}$$

$$\beta_{i,UCF} = \mathrm{E}\left[(R_{it}-\mu_i)N_{CF,t}\middle|\, u_{mt}\geq 0\right] \;/\; \mathrm{E}\left[u_{mt}^2\middle|\, u_{mt}\geq 0\right], \tag{11}$$

$$\beta_{i,UDR} = -\mathrm{E}\left[(R_{it}-\mu_i)N_{DR,t}\middle|\, u_{mt}\geq 0\right] \;/\; \mathrm{E}\left[u_{mt}^2\middle|\, u_{mt}\geq 0\right], \tag{12}$$

By differentiating between the covariance of returns with the discount rate and cash flow factor in up and down markets, respectively, we can control for risk factors in both dimensions simultaneously. Note that the definitions in (9) through (12) are completely analogous to (4) and (5). The main difference is that we have conditioned the expectations on the unexpected market return u_{mt} being positive or negative. As the unexpected market return has zero mean by construction, zero is also the natural cut-off point to distinguish up from down markets. Also note that by construction, the discount rate and cash flow factors have zero means as they are directly based on the innovations u_t in (8).

The four different betas in (9) through (12) can now be used in standard asset pricing tests. In particular, we test the explanatory power of our new four-beta decomposition,

$$\mathrm{E}_t[R^e_{i,t+1}] = \alpha_1 + \lambda_{DCF}\cdot\beta_{i,DCF} + \lambda_{DDR}\cdot\beta_{i,DDR} + \lambda_{UCF}\cdot\beta_{i,UCF} + \lambda_{UDR}\cdot\beta_{i,UDR}, \tag{13}$$

where $R^e_{i,t+1}$ denotes the excess return (over the risk-free rate) for asset i, α_i is the intercept for asset i, and λ_j is the price of risk for $\beta_{i,j}$ for $j = DCF, DDR, UCF, UDR$. We benchmark our results to the simpler two-way decompositions of beta of Ang et al. (2006) and Campbell and Vuolteenaho (2004).

In our empirical analysis in Section 4 we follow Black, Jensen, and Scholes (1972), Gibbons (1982), and Ang, Chen, and Xing (2006), by testing the contemporaneous relationship between betas and the realized average return (as a proxy for expected return). We perform Fama-MacBeth regressions with time-varying betas estimated over 60-month rolling windows from July 1963 to December 2008. In this way, we can compute a time series of the risk premia corresponding to the time-varying betas. The test then considers whether the mean of the time series of risk premia is positive and significantly different from zero. We use overlapping windows to estimate the betas, and heteroskedasticity and autocorrelation consistent (HAC) standard errors for our pricing tests, see Andrews (1991).

3 Data

A return decomposition based on a VAR model should contain state variables with sufficient predictive ability. As argued by Campbell et al. (2010), Engsted et al. (2010), and Chen (2010), it is particularly important to include dividend yields in the analysis to reduce the sensitivity of the results to the precise VAR model used. We therefore specify the following three variables in our VAR model: (i) the log excess market return defined as the log of the CRSP value weighted market index minus the log of the three-month Treasury bill rate; (ii) the three-month Treasury bill rate itself; and (iii) the dividend yield on the S&P 500 composite price index calculated from data provided on Robert Shiller's website. In their original paper, Campbell and Vuolteenaho (2004) also stress the importance of the small stock value spread as an important element of their VAR model. Over the sample period used in our paper (1963–2008), however, the variable turns out to be statistically insignificant and we exclude it from the further analysis.

The ability of the dividend yield to predict excess expected returns has been largely accepted and documented in the finance literature, see for example Campbell (1991), Cochrane (1992, 2008), and Lettau and Ludvigson (2001). Ang and Bekaert (2007) point out that this is best visible at short horizons by specifying the short-term interest rate as an additional regressor. They are more skeptical about the predictive power of dividend yields in the long-term. We therefore also include the short-term interest rate in our analysis.

Table 1 shows the VAR parameter estimates. Both the short-term interest rate and the dividend yield are higly persistent and have a statistically significant impact on stock returns. As expected, higher interest rates have a negative impact on returns, while the relation between dividend yields and returns is positive.

[INSERT TABLE 1 HERE]

Using the VAR model from Table 1, we construct the cash flow ($N_{CF,t}$) and discount rate ($N_{DR,t}$) news factors from the VAR residuals using equation (8). The variance covariance matrix of the news factors is presented in Table 2. The variance of DR news is almost twice the size of the CF news variance. Campbell (1991) finds similar results with the discount rate news being the dominant component of market return variance.

[INSERT TABLE 2 HERE]

The test assets we use in our pricing regressions are individual stocks rather than portfolios. The use of portfolios rather than individual stocks in the cross-sectional Fama-MacBeth regressions is rather standard to mitigate the errors-in-variables problem caused by the use of estimated rather than true betas. However, this advantage comes at the cost of a significant loss of efficiency due to the reduced cross-sectional spread of estimated betas. This is particularly relevant in our current context. As our model tries to identify the separate pricing components of four beta-related components, the use of portfolios results in too much multi-collinearity in the cross-sectional estimation step of the Fama-MacBeth procedure. Correlations between estimated up, down, cash flow, and discount rate betas are in excess of 95%. As a result, the risk premia estimates become unstable.

Ang et al. (2008) show analytically and empirically that the conclusions drawn from individual versus portfolio test assets can differ substantially due to the trade-off between bias and efficiency. They also indicate that the use of individual stocks as test assets generally permits better asset pricing tests and estimates of risk premia. We therefore follow their conclusion that there is no particular reason to create portfolios when just two-pass cross-sectional regression coefficients are estimated, and that it is preferrable to run the asset pricing tests in such cases based on individual stocks. All tests presented in the next section are therefore based on all individual common stocks traded on the NYSE, AMEX and NASDAQ over the period July 1963 to December 2008 (share codes 10 or 11 in the CRSP database). In our robustness checks we vary the sample period as well as the sampling frequency to see whether our baseline results remain valid. For the analyses based on monthly data, we use data from the CRSP-Compustat merged database in WDRS. For the analyses based on quarterly data, we take all available data from the CRSP database.

4 Empirical Results

4.1 Baseline Results

Table 3 presents our baseline results. The first 60-month window spans July 1963 to June 1968 and the last January 2004 to December 2008; so we analyze 486 overlapping 60-months windows in total. The number of stocks in each cross-section varies from 383 in earlier periods to 3,703 in later periods. In order to ensure that extreme outliers do not drive the results, we winsorize returns in each window at the 1% and 99% level.

[INSERT TABLE 3 HERE]

Column I in Table 3 shows that the standard beta has a significant and positive premium. When we decompose the beta in an up and a down beta as in column II, we see that both betas carry a significant premium at the 1% and 5% level, respectively. The average premium for the downside beta is almost six times that for the upside beta. Model III presents the results for the cash flow and discount rate beta model. Both cash flow and discount rate betas are priced significantly, but there appears to be no significant difference between the two premia, compare Campbell and Vuolteenaho (2004).

Model IV presents the results for our new four-beta model. The downside cash flow (DCF) and downside discount rate (DDR) betas carry the largest premia and are significant at the 1% level. The upside cash flow (UCF) and upside discount rate (UDR) betas are also significant at the 5% and 10% level, respectively, but the size of the DCF and DDR premia are about three times as high as the UCF and UDR premia. So both cash flow (CF) and discount rate (DR) betas are priced more in down than in up markets. Interestingly, the downside CF beta carries the largest premium. This is in line with our intuition. From Ang et al. (2006) we expect investors to charge higher premia for downside risk. From Campbell and Vuolteenaho (2004), on the other hand, we expect a larger premium for CF betas. Our results show that both these effects have explanatory power in the cross-section, and exposure to downside CF news carries the largest premium. It is also clear that the four-fold beta decomposition provides additional information here: in the standard two-fold decomposition of CF versus DR (model III), we find no significant difference in premia.

To investigate whether our baseline results are robust to size and book-to-market effects, we respecify our models I to IV by adding the Fama and French (1992) size and book-to-market factors to the cross-sectional regressions.[2] To account for influential observations, we also winsorize the size and book-to-market controls at the 1% and 99% level. The columns V to VIII of Table 3 show that the premia estimates are robust to controling for size and book-to-market effects. There appears to be a mild shift downward in the DCF premium, and an upward shift in the UCF and UDR premia. All shifts fall well within the two standard error bands. In particular, the relative magnitudes and the statistical significance remain unaltered. Consistent with Fama and French (1992), we find a robust and significantly negative premium for size, and a significantly postitive premium for book-to-market.

To investigate the time series properties of the premia estimates, we re-estimate our four-beta model over the different decades in our sample. Each of the four subperiods describes a different episode of the stock market. During the 1970s, the U.S. economy was hit by several recessions, including the two major oil price crises. During the 1980s, the US economy suffered by the savings and loans crisis. In the 1990s U.S. equity experienced a strong bull market. This rally led to the burst of the tech bubble in early 2000 followed by the financial crises at the end of our sample period 2007-2008. Panel A of Table 4 shows the results.

[INSERT TABLE 4 HERE]

Comparing the premia for the DCF and the UCF beta, we find that the DCF beta is robustly priced in all four subsamples. The UCF beta, however, is only significantly priced during the stock market rally of the 1990s. The DDR and UDR premia show opposite and trending results over time. Sensitivity to downside discount rate news is priced high in the cross-section at the start of our sample and during the 1980s. Over the 1990s and 2000s, however, the price declined and even becomes insignificant during the last decade. By contrast, the sensitivity to upside discount rate news carries a negative price in the early years of the sample, but gradually increases over time to a positive and significant premium in the 2000s. During this last decade, the UDR premium even is the largest of the four premia.

Overall, our subsample analysis indicates that downside betas are priced more robustly than upside betas, which is consistent with our previous results over the whole sample period of 1963 to 2008. Considering the UDR beta, we obtain mixed evidence of positive and negative

[2] Size is the log market capitalization at the start of each 60-month window. For book-to-market, we follow Fama and French (1992): for January till June of year t, we take the book value end-December of year $t-2$, and for July till December of year t, we take the book value end-December of year $t-1$. The book value is then divided by the current market value of equity.

premia in different periods. The only beta component that is robustly priced throughout all subsamples remains the DCF beta.

To control further for possible size and book-to-market effects, we test our factor models using five subsamples constructed by sorting the data with respect to size and book-to-market, respectively. First, we sort our sample based on market capitalization (respectively book-to-market) at the beginning of each 60-month window of the Fama-MacBeth estimation procedure and divide the cross-section into five quintiles. Then, we compute our estimate of the premium by running the cross-sectional regressions for each of the five quintiles separately.

Panel B of Table 4 shows a clear effect of size on the estimated premia for the four-beta model. The DDR beta premium is lower for the largest two quintiles, and the decline is statistically significant. For the DCF premium, the decrease for large cap companies is much less strong, though also statistically significant. For the UDR and UCF premia, we see a much more constant pattern across size quintiles. In particular, there is no statistically significant difference between the premia estimates for large versus small companies, though the UCF premium shows a mild increase for increasing company size.

Comparing the relative magnitudes of the different premia, we see that for small companies the downside components are dominant pricing ingredients. For large companies, however, it is predominantly the cash flow component that is relevant. In particular, the impact of the cash flow component appears more symmetric, with the magnitude of the premia for DCF and UCF being roughly the same. This suggests that the notion of downside risk is much more relevant for small companies, irrespective of whether this is downside cash flow or downside discount rate risk. If well-established companies are considered, a much more symmetric notion of stock market risk appears to apply, mainly relating to cash flow rather than to discount rate news.

Panel C of Table 4 displays the results for the book-to-market quintiles. In contrast to the results in panel B, we do not observe a clear pattern. Only the DCF premium appears to be somewhat larger for the highest book-to-market quintile, and the difference with the other quintiles is significant at the 5% level. We do see the higher premia again for the downside factors compared to the upside ones. The downside premia are two-fold up to five-fold their upside counterparts. The downside cash flow premium is higher than the downside discount rate premium. The difference is significant for the higher book-to-market quintiles. For the upside premia UDR and UCF, there is no such clear difference. Again, we conclude that downside cash flow risk is consistently priced and carries the largest premium, followed by downside discount rate risk. The upside risk factors are less consistently priced and smaller in magnitude.

Overall, both asymmetric preferences for downside versus upside risk as well as for long-term versus short-term risk play a major role in explaining the cross-section of stock returns. Our new four-beta model helps to isolate the effect of these different components on market risk premia. The baseline results show that both DCF and DDR betas are priced more robustly in the cross-section, while both UCF and UDR betas are not priced consistently. The only component that is priced robustly over all samples is the DCF beta. Downside betas have larger premia than their upside counterparts in most sub-samples. However, downside risk particularly appears to be a concern for small stocks. Expected returns for largers stocks appear to be driven more by a symmetric notion of cash flow risk.

4.2 Robustness Analysis

So far, we computed discount rate news (as the change in the discounted sum of future expected returns) directly, treating CF news as the residual outcome, i.e., as the unexpected market return minus the computed DR news factor. Chen and Zhao (2009) argue that such a definition of cash flow news influences the size of premia estimates. Campbell, Polk, and Vuolteenaho (2010), Chen (2010), and Engsted, Pedersen, and Tanggaard (2010), however, show that the sensitivity of premia estimates and factor sensitivities to the decomposition method used is reduced considerably by including the dividend yield in the underlying VAR model. Still, to check the sensitivity of our results, we follow Chen and Zhao (2009) and investigate the robustness of our four-beta model to alternative decomposition methods. In particular, we build an additional VAR model to construct CF news directly, rather than as a residual. For more details, we refer to Chen and Zhao (2009).

The VAR model for dividend growth takes the lagged dividend growth rate and the lagged market excess returns as explanatory variables. To reduce seasonality issues while retaining a reasonable number of observations for the time series regressions, we use quarterly rather than monthly (or annual) data from 1963:Q3 to 2008:Q4. The CF news component at time $t+1$ is computed as

$$N^{\mathrm{dir}}_{CF,t+1} = e_1' \Lambda_2 \nu_{t+1}, \tag{14}$$

where $\Lambda_2 = (\mathrm{I} - \rho\Gamma_2)^{-1}\Gamma_2$; Γ_2 is the coefficient matrix of the VAR model for dividend growth, ν_{t+1} denotes the vector of VAR residuals, and the first element in this second specified VAR model is the dividend growth. We can compute the correlation between our direct estimate of cash flow news $N^{\mathrm{dir}}_{CF,t}$ from (14) with our previous indirect estimate $N_{CF,t}$. As in Chen and Zhao (2009), the correlation between the two estimates is far from perfect. In our case the correlation is only 0.291. Part of this low correlation may be due to the simple VAR model used to construct the direct estimate of cash flow news, as the dividend growth rate is notoriously difficult to model. Despite this low correlation, the results presented below indicate that the consistent significance of downside cash flow news as a priced risk factor survives. The current analysis therefore provides a strong robustness check for our claims on the relevance of the downside cash flow in stock returns.

As a further robustness check, we also compute the results with an alternative computation for the discount rate news component. As mentioned earlier, we originally computed $N_{DR,t}$ directly, and computed $N_{CF,t}$ as the residual. With our new $N_{CF,t}^{\text{dir}}$ cash flow risk factor, we can also take the opposite perspective and define $N_{DR,t}$ as a residual. We do so by defining

$$-N_{DR,t}^{\text{res}} = u_{mt} - N_{CF,t}^{\text{dir}}, \tag{15}$$

with u_{mt} the unexpected return from the VAR model for returns, see Section 2.2. The correlation between the indirect DR news factor $N_{DR,t}^{\text{res}}$ and the original, direct DR news factor $N_{DR,t}$ is again not perfect with a value of 0.823. Interestingly, however, the construction of the discount rate news factor appears less sensitive to the decomposition method used.

We first discuss Panel A in Table 5. Panel B is discussed in Section 4.3. Panel A shows the results for our three different decomposition methods. We use a 40-quarter rolling window to estimate different betas and average returns, resulting in 143 overlapping windows. Because we only use price data in this exercise, the number of stocks varies from 1,158 to 2,678 per cross-section as we do not loose observations by matching CRSP price data with Compustat book value data.

[INSERT TABLE 5 HERE]

We see that the DCF, DDR and UDR betas always have a positive and significant premium irrespective of the decomposition method used. The estimates of the DCF and DDR premia are larger than their UCF and UDR counterparts, implying the downside risk dimension is more important, irrespective of the decomposition method used. We also note that the UCF factor is not consistently priced across decomposition methods. This reinforces our conclusion regarding the price impact of downside risk.

It becomes also clear that the choice of the decomposition method influences the size of the premium estimates. Particularly the DCF premium, and to a lesser extent the DDR premium, is higher if a direct measure of cash flow news is used. The larger price for downside risk under the alternative decomposition methods is in line with our earlier results that the downside risk components, and the downside cash flow related parts in particular, carry the largest price.

4.3 Economic Significance

So far, we have focused on the premia estimates λ_j for $j = DCF, DDR, UCF, UDR$. The expected returns, however, are a composite of these premia and their associated β_{ij}s. For example, it might well be that higher premia are partly off-set by lower average levels of β for a particular segment of the stock market. In order to provide more insight into the economic magnitude of the product of betas and their premia, we perform the following analysis. For each window of the Fama-MacBeth procedure, we compute the product of the premium estimate and the cross-sectional average beta over that window. In this way, we obtain the contribution of risk factor j to the overall expected return in rolling window t. Subsequently, we compute the time series averages of all these contributions and their HAC standard errors.

The most right-hand column in Panel A of Table 6 shows that over the complete sample period 1963–2008 the expected return component $\lambda_j \times \beta_j$ is again largest for the downside components $j = DCF, DDR$. Moreover, the downside components are statistically significant, whereas the upside components UCF and UDR are not. In contrast to some of our earlier results for the premia λ_j (see Table 3), the product of betas and premia is larger for the DDR factor than for the DCF component. The higher premium on average for DCF that we observed in Table 3 is thus off-set by a lower average DCF beta compared to the DDR beta.

Comparing the results for the different decades in the sample, we see that the expected return component for DDR is stable over most of the sample, except during the 2000s. Over the last decade, the significance level drops to 10% and the component becomes slightly negative. The opposite holds for the UDR factor. Both results are in line with our earlier findings for risk premia only (see Table 4). The altered monetary regime over the 2000s combined with the bear markets during the burst of the dotcom bubble in the year 2000 and the 2007-2008 financial crisis significantly affect the premia estimates for discount rate news.

Comparing the DCF and DDR expected return components, we see that the contribution of downside discount rates to expected returns is higher up to the year 2000. Over the most recent period, the DCF is the dominant factor in expected returns. We also note that the DCF component is consistently and significantly positive, though its magnitude over the different periods differs. All other pricing components, by contrast, show statistically significant changes of sign over time. This supports our earlier view of DCF as the most consistently priced factor in the data.

[INSERT TABLE 6 HERE]

In order to control for the possible size effect as documented in Table 4, we also calculate the expected return components using five size-sorted subsamples. Our empirical findings in Panel B of Table 6 indicate once more a substantial and significant size effect. For small companies, both DCF and DDR betas capture the expected returns, with the DDR component twice the size of its DCF counterpart. Again, we conclude that downside cash flow risk carries the largest premium, but firms' exposures to this risk factor on average are smaller, such that the downside discount rate risk makes up a larger fraction of the average returns.

For the large companies, average returns cannot be explained by downside or upside preferences, nor by the long-term versus short-term decomposition. Though the components are significant at (only) the 10% level, they are economically small.

Finally, computing the components across decomposition methods, we obtain the results in Panel B of Table 5. Interestingly, the same pattern emerges. Though downside cash flow risk carries the largest premium, the dominant contribution of downside cash flow news sensitivity to averate returns hinges on the use of decomposition method I, i.e., based on direct discount rate new modeling. If direct measures of cash flow news are used as in methods II and III, downside and upside discount rate news are more important contributors to average returns. In terms of statistical significance, only the UCF component appears not robust.

4.4 Betas and Future Returns

Our final test is the most challenging one and provides an out-of-sample robustness check. In testing factor models using Fama-Macbeth regressions, different proxies can be taken for the expected return. So far, we have followed the approach of Lettau and Ludvigson (2001) and Ang et al. (2006) and used in our cross-sectional regressions estimated betas and average returns that were measured over the same data window. We label this approach model I. Alternatively, however, we could use the betas over the estimation window to forecast the next month's out-of-sample return. We label this as model II. This is a substantial step, as 1-month returns are obviously much noisier proxies of expected returns than 5-year averages of monthly returns. One can thus expect the results to become less clear than in previous sections.

We also specify another model. The cross-sectional regressions in this model III use the betas from the estimation window to forecast the return average of the next 60-months out-of-sample returns. This proxy should be of similar quality as that of model I. The crucial difference, however, is that model I checks the in-sample predictive power of betas, whereas model III tests the out-of-sample predictive power. The results are presented in Table 7.

[INSERT TABLE 7 HERE]

The results for model I are the same as presented earlier. As expected for model II, the data is very noisy. As a result, hardly any of the estimates are statistically significant. The estimates of the downside risk components DDR and DCF have the correct sign. Their magnitude, however, has decreased substantially, whereas the standard errors have gone up. The higher standard errors are a natural consequence of the fact that 1-month returns are very noisy proxies of expected returns. The upside components have an estimated negative premium. For the upside discount rate factor, the estimate is even statistically significant.

If we take average returns over 60-months rather than over 1-month out-of-sample as our dependent variable in the cross-sectional regressions (as in model III), results become clear again. The DCF beta is the only one that is priced significantly, and it carries a positive premium of around 3.5% p.a. This is smaller than the in-sample estimate of around 6%, but still substantial. All point estimates of the other premia are very close to zero, and only one of them is significant at the 10% level (UCF). We also note that the standard errors for model III are again in line with those for model I.

The results are very supportive of the DCF factor as carrying the largest and most consistent premium, not only in-sample, but also out-of-sample. The results are further confirmed if we add the size and book-to-market controls to the regressions as in models IV–VI. As expected, the size of the DCF premium is somewhat reduced, but it remains the only significant premium estimate among the four beta related premia.

Overall, in an out-of-sample context, the results again support our major finding that investors want to be compensated for downside risk. The required compensation can mainly be attributed to the downside cash flow component.

5 Conclusions

Through a decomposition of the simple CAPM beta into four components (downside and upside cash flow (DCF and UCF) betas and downside and upside discount rate (DDR and UDR) betas) we show that we can increase our understanding of the types of risk that investors want to be compensated for. Using individual U.S. stock returns over the period 1963-2008, we see that the downside cash flow risk is most consistently priced in our sample. Downside discount rate risk is next in line, followed by upside cash flow risk and upside discount rate risk, respectively. The results survive a range of robustness checks with respect to sampling periods, use of controls, and use of decomposition methods. In particular, the DCF premium is the only robust premium of the four beta premia in an in-sample versus out-of-sample comparison.

Interestingly, we find that the downside cash flow risk compensation is intimately linked with the small stock premium. Particularly for small-sized companies, the DCF beta appears an important pricing determinant. For larger companies, a much more symmetric notion of risk (both upside and downside) applies, and the cash flow rate news component appears to dominate the discount rate component. It thus appears that downside risk is mainly relevant for small stocks, and then downside cash flow risk in particular. Apparently, differences in the investor base of large versus small stocks cause the relevance of asymmetric preferences to be less relevant in the large stock segment.

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Table 1: VAR Parameter Estimates for the Return Decomposition Model

The table shows the OLS estimates of the vector autoregressive (VAR) model (6). The dependent variables are log excess market return ($R^e_{m,t}$), the short-term interest rate (SR_t), and the dividend yield (DY_t). Standard errors are given in parentheses. ***, **, and *, denote significance at the 1, 5, and 10 percent level, respectively.

	Intercept	$R^e_{m,t}$	SR_t	DY_t	R^2%
$R^e_{m,t+1}$	-0.004	0.089**	-0.199***	0.539***	3.04
	(0.005)	(0.038)	(0.067)	(0.162)	
SR_{t+1}	0.001	0.007*	0.992***	-0.012	97.5
	(0.001)	(0.004)	(0.007)	(0.017)	
DY_{t+1}	0.000*	-0.015***	0.004***	0.987***	99.2
	(0.000)	(0.001)	(0.002)	(0.004)	

Table 2: Variance-Covariance Matrix of Cash Flow and Discount Rate News

The table shows the variance covariance matrix of the unexpected market return (u_{mt}) and its two components, cash flow (CF) news and discount rate (DR) news, using the three-variable VAR model from Table 1. The VAR model includes the excess market return R_{mt} (above the risk-free rate), the short (3 month) rate SR_t, and the S&P500 dividend yield DY_t.

	u_{mt}	$N_{CF,t}$	$N_{DR,t}$
u_{mt}	0.0018	0.0006	0.0012
$N_{CF,t}$	0.0006	0.0007	-0.0001
$N_{DR,t}$	0.0012	-0.0001	0.0013
Mean	0.0013	0.0082	-0.0069

Table 3: Baseline Risk Premia Estimates

The table shows the time series average and its HAC standard errors (in parentheses) of the Fama-MacBeth premia estimates λ_{jt}, where t denotes 60-month rolling window t and j denotes the risk factor, j being downside (D), upside (U), cash flow (CF), discount rate (DR), downside cash flow (DCF), downside discount rate (DDR), upside cash flow (UCF), and upside discount rate (UDR) risk, respectively. The sample consists of monthly returns for all listed companies on the NYSE, AMEX and NASDAQ exchanges from July 1963 to December 2008 (546 months), using the CRSP-Compustat merged database in WDRS. There are 486 sixty-months overlapping estimation windows in the sample. Stocks with one or more missing data points in a specific rolling window, we deleted all stocks that had one or more missing data in that window. The number of stocks in each cross-sectional regression varies from 383 to 3,703. Returns in each window are winsorized at the 1% level and 99% level. ***, **, and *, denote significance at the 1, 5, and 10 percent level, respectively.

	I	II	III	IV	V	VI	VII	VIII
α	0.299***	0.273***	0.314***	0.293***	0.706***	0.674***	0.787***	0.768***
	(0.064)	(0.064)	(0.063)	(0.063)	(0.210)	(0.210)	(0.208)	(0.203)
λ	0.474***				0.516***			
	(0.057)				(0.047)			
λ_D		0.420***				0.386***		
		(0.051)				(0.039)		
λ_U		0.071***				0.148***		
		(0.034)				(0.036)		
λ_{CF}			0.507***				0.603***	
			(0.073)				(0.076)	
λ_{DR}			0.526***				0.591***	
			(0.087)				(0.075)	
λ_{DCF}				0.525***				0.480***
				(0.062)				(0.054)
λ_{DDR}				0.378***				0.385***
				(0.066)				(0.049)
λ_{UCF}				0.130***				0.253***
				(0.065)				(0.058)
λ_{UDR}				0.088***				0.161***
				(0.048)				(0.052)
Size					-0.060***	-0.059***	-0.066***	-0.065***
					(0.015)	(0.015)	(0.014)	(0.014)
B/M					0.323***	0.327***	0.315***	0.319***
					(0.026)	(0.026)	(0.026)	(0.025)
R^2	0.072	0.082	0.084	0.102	0.144	0.151	0.153	0.167

Table 4: Subsample Analysis

The table shows the premia estimates and their standard errors as in Table 3, but for different subsamples. Panel A shows the results for different decades. In Panel B, we sort all companies for each rolling window based on their market capitalization at the beginning of the period and construct 5 quintiles. In Panel C, we sort all companies based on their book-to-market value at the beginning of each rolling window. Premia are computed for each quintile. ***, **, and *, denote significance at the 1, 5, and 10 percent level, respectively.

Panel A: Sample Periods					
	1970s	1980s	1990s	2000s	1963-2008
α	0.085	0.191**	0.240**	0.805***	0.293***
	(0.076)	(0.092)	(0.115)	(0.124)	(0.063)
λ_{DCF}	0.246**	1.007***	0.642***	0.209*	0.525***
	(0.096)	(0.086)	(0.091)	(0.118)	(0.062)
λ_{DDR}	0.473***	0.579***	0.194***	0.093	0.378***
	(0.149)	(0.101)	(0.068)	(0.111)	(0.066)
λ_{UCF}	0.228	-0.032	0.432***	-0.009	0.130**
	(0.199)	(0.044)	(0.069)	(0.057)	(0.065)
λ_{UDR}	-0.315***	-0.015	0.159***	0.526***	0.088*
	(0.055)	(0.045)	(0.031)	(0.112)	(0.048)

Panel B: Size					
	Small	2	3	4	Large
α	0.327***	0.186**	0.310***	0.451***	0.472***
	(0.094)	(0.078)	(0.071)	(0.050)	(0.050)
λ_{DCF}	0.586***	0.573***	0.553***	0.355***	0.228**
	(0.047)	(0.061)	(0.084)	(0.110)	(0.106)
λ_{DDR}	0.620***	0.469***	0.325***	0.058	0.066
	(0.061)	(0.070)	(0.057)	(0.069)	(0.105)
λ_{UCF}	0.186***	0.273***	0.251***	0.361***	0.285***
	(0.050)	(0.072)	(0.067)	(0.067)	(0.078)
λ_{UDR}	0.149***	0.142**	0.123	0.153**	0.084
	(0.028)	(0.061)	(0.075)	(0.074)	(0.069)

Panel C: Book-to-Market (B/M)					
	Low	2	3	4	High
α	-0.136	0.040	0.186***	0.389***	0.491***
	(0.085)	(0.066)	(0.060)	(0.062)	(0.074)
λ_{DCF}	0.556***	0.462***	0.534***	0.553***	0.775***
	(0.088)	(0.078)	(0.073)	(0.064)	(0.068)
λ_{DDR}	0.464***	0.547***	0.377***	0.308***	0.422***
	(0.071)	(0.068)	(0.069)	(0.073)	(0.069)
λ_{UCF}	0.188***	0.153**	0.210***	0.134**	0.167***
	(0.072)	(0.072)	(0.066)	(0.061)	(0.063)
λ_{UDR}	0.112*	0.194***	0.225***	0.179***	0.069**
	(0.062)	(0.064)	(0.053)	(0.045)	(0.033)

Table 5: Robustness Analysis for Alternative Decompostion Methods

Panel A shows the Fama-MacBeth premia estimates λ_j and their HAC standard errors (in parentheses) for j equal to downside cash flow (DCF), downside discount rate (DDR), upside cash flow (UCF), and upside discount rate (UDR) risk, respectively. The estimates are based on three different decomposition methods for computing cash flow and discount rate news. The sample contains quarterly return data for all listed companies on the NYSE, AMEX and NASDAQ exchanges over July 1963 to December 2008 (182 quarters). We use a 40-quarter rolling window to estimate betas and average returns. Stocks with one or more missing data points in a specific estimation window, are deleted from the cross-sectional regression for that cross-sectional window. The number of stocks varies from 1,158 to 2,678 over the sample. Method I uses a direct measure for discount rate news and an indirect measure for cash flow news as in (8). Method II uses a direct measure for discount rate news and a direct measure for cash flow news as in (14). Method III uses an indirect measure for discount rate news and a direct measure for cash flow news as in (15). Panel B reports the time series average and its HAC standard errors of $\lambda_{jt} \cdot \bar{\beta}_{jt}$, where $\bar{\beta}_{jt}$ is the cross-sectional mean of beta for risk factor j over the 40-quarter rolling window t, and λ_{jt} is the premium estimate for risk factor j over the same window. ***, **, and *, denote significance at the 1, 5, and 10 percent level, respectively.

	Panel A: Premium Estimates			Panel B: Expected Return Contributions ($\lambda \cdot \bar{\beta}$)		
	I	II	III	I	II	III
α	0.825***	1.309***	0.868***			
	(0.196)	(0.226)	(0.197)			
λ_{DCF}	1.931***	3.790***	2.487***	0.851***	0.258***	0.144***
	(0.190)	(0.555)	(0.514)	(0.082)	(0.051)	(0.035)
λ_{DDR}	0.868***	1.391***	1.267***	0.596***	0.926***	1.325***
	(0.110)	(0.140)	(0.100)	(0.078)	(0.094)	(0.113)
λ_{UCF}	0.769***	-0.133	0.098	0.315***	0.034*	0.008
	(0.143)	(0.283)	(0.238)	(0.069)	(0.018)	(0.015)
λ_{UDR}	0.601***	0.702***	0.582***	0.405***	0.465***	0.648***
	(0.081)	(0.105)	(0.096)	(0.051)	(0.065)	(0.111)

Table 6: Expected Return Contribution for Monthly Data

The data and set-up used for this table are the same as for Tables 3 and 4. The table shows the time series average and its HAC standard errors (in parentheses) of $\lambda_{jt} \cdot \bar{\beta}_{jt}$, where $\bar{\beta}_{jt}$ is the cross-sectional mean of beta for risk factor j over the 60-month rolling window t and λ_{jt} is the premium estimate for risk factor j, respectively, with j equal to downside cash flow (DCF), downside discount rate (DDR), upside cash flow (UCF), and upside discount rate (UDR) risk, respectively. Panel A splits the sample period in different decades. Panel B uses size sorted subsamples. ***, **, and *, denote significance at the 1, 5, and 10 percent level, respectively.

	Panel A: Sample Periods				
	1970s	1980s	1990s	2000s	1963-2008
λ_{DCF}	0.079*	0.218***	0.087*	0.523***	0.212***
	(0.043)	(0.041)	(0.037)	(0.081)	(0.034)
λ_{DDR}	0.343***	0.561***	0.396***	-0.075*	0.353***
	(0.105)	(0.060)	(0.062)	(0.048)	(0.050)
λ_{UCF}	0.034*	-0.023*	0.064***	0.062***	0.028*
	(0.064)	(0.010)	(0.018)	(0.021)	(0.019)
λ_{UDR}	-0.070*	-0.001*	-0.045***	0.164***	0.023*
	(0.047)	(0.026)	(0.015)	(0.034)	(0.021)

	Panel B: Size				
	Small	2	3	4	Large
λ_{DCF}	0.202***	0.196***	0.187***	0.096*	0.055*
	(0.021)	(0.027)	(0.035)	(0.040)	(0.040)
λ_{DDR}	0.445***	0.367***	0.219***	0.010*	-0.008*
	(0.048)	(0.051)	(0.040)	(0.047)	(0.056)
λ_{UCF}	0.014*	0.052*	0.055*	0.102***	0.072*
	(0.015)	(0.022)	(0.026)	(0.024)	(0.028)
λ_{UDR}	0.051*	-0.013*	-0.022*	0.012*	-0.024*
	(0.020)	(0.040)	(0.048)	(0.046)	(0.040)

Table 7: Current Betas and Future Expected Returns

The table shows the time-series means and corresponding HAC standard errors (in parentheses) of Fama-MacBeth estimates of the premia for downside cash flow (DCF), downside discount rate (DDR), upside cash flow (UCF), and upside discount rate (UDR) risk. Model I uses the cross-sectional Fama-MacBeth regressions based on 60-month rolling window estimates of betas and average returns over the same rolling window. Model II uses the same betas, but uses the next month's return following the rolling window as its dependent variable. Model III uses the average of the next 60 month out-of-window returns as the dependent variable. Models IV to VI are similar to I to III, but also include size and book-to-market controls. The data is the same as for Table 3. ***, **, and *, denote significance at the 1, 5, and 10 percent level, respectively.

	I	II	III	IV	V	VI
	60m in-sample	1m out-of-sample	60m out-of-sample	60m in-sample	1m out-of-sample	60m out-of-sample
α	0.293***	0.577***	0.698***	0.768***	0.045	1.113***
	(0.063)	(0.183)	(0.057)	(0.203)	(0.527)	(0.194)
λ_{DCF}	0.525***	0.221	0.307***	0.480***	0.153	0.209***
	(0.062)	(0.215)	(0.050)	(0.054)	(0.193)	(0.037)
λ_{DDR}	0.378***	0.192	-0.056	0.385***	0.292*	0.024
	(0.066)	(0.184)	(0.045)	(0.049)	(0.161)	(0.035)
λ_{UCF}	0.130**	-0.109	-0.072*	0.253***	0.000	0.026
	(0.065)	(0.115)	(0.037)	(0.058)	(0.097)	(0.033)
λ_{UDR}	0.088*	-0.236**	-0.010	0.161***	-0.237***	0.001
	(0.048)	(0.093)	(0.035)	(0.052)	(0.082)	(0.028)
Size				-0.065***	0.017	-0.049***
				(0.014)	(0.037)	(0.015)
B/M				0.319***	0.347***	0.210***
				(0.025)	(0.074)	(0.019)

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