GOOD, BAD, UP, AND DOWN BETAS: WHAT IS ACTUALLY PRICED?*

Mahmoud Botshekan[a,d] **Roman Kraeussl**[a] **Andre Lucas**[a,b,c]

(a) Department of Finance, VU University Amsterdam

(b) Duisenberg School of Finance, Amsterdam

(c) Tinbergen Institute, Amsterdam

(d) Department of Management, University of Isfahan

January 2010

Abstract

Stock returns are determined both by news about cash flows and news about discount rates (Campbell and Vuolteenaho (2004)). In this paper we test whether asymmetric preferences for losses versus gains like in Ang, Chen, and Xing (2006) also affect the pricing of cash flow versus discount rate news. For this, we construct a new four-fold beta decomposition, distinguishing cash flow and discount rate betas in both up and down markets. We test which of the four betas is priced most consistently in the cross-section of CRSP stock returns. Our results indicate that the downside cash flow beta and downside discount rate beta carry the largest premium. We subject our result to an extensive number of robustness analyses, including the alternative decomposition methods for cash flow and discount rate news of Chen and Zhao (2008). The downside cash flow risk is priced most consistently across samples, periods, and methodologies. The cash flow premia estimates decrease with company size. Moreover, in terms of their economic contribution in explaining the level of average realized returns, it appears that the importance of both up and down discount rate news dominates the contribution of downside cash flow risk.

JEL codes: G11, G12, G14

Keywords: downside risk, upside risk, cash flow risk, discount rate risk, asset pricing

* Corresponding author: Andre Lucas, VU University Amsterdam, FEWEB/FIN, de Boelelaan 1105, 1081 HV Amsterdam, Netherlands, phone: +31 20 598 6039, fax: +31 20 598 6020, email: alucas@feweb.vu.nl.

I. Introduction

The CAPM model of Sharpe (1964), Linter (1965) and Black (1972) provides a simple and intuitive model for describing the relationship between risk and return. It serves as a useful benchmark in modern asset pricing theory, for estimating the cost of capital, and for evaluating the risk corrected performance of managed portfolios. However, the shortcomings of the model are also well known. There is an extant empirical literature showing that the CAPM in its simplest form is not a good predictor of expected returns, see for example Fama and French (1992).

In this paper we start with the extension of the basic CAPM as introduced by Campbell and Vuolteenaho (2004). They extend the basic CAPM and its beta into two different risk factors: one relating to discount rate risk, and one related to cash flow risk. They argue that in an economy with many long-term rather than short-term investors, cash flow risk should carry a larger premium than discount rate risk. The intuition is that for long-term investors the negative impact of surprise discount rate increases on current realized returns is off-set by higher future expected returns. Using this two-fold decomposition, they define a good beta (i.e., sensitivity to discount rate news) and a bad beta (i.e., sensitivity to cash flow news). This distinction between different types of betas helps to partially explain some of the existing pricing anomalies, like the size and value effect.

In this paper, we further refine the pricing model of Campbell and Vuolteenaho (2004) by distinguishing the price of cash flow and discount rate risk between up and down markets. This distinction follows naturally from the work by Ang et al. (2006) and links to the well-known literature that claims that investors typically are loss averse, see for example Hogan and Warren (1974), Bawa and Lindenberg (1977) and Harlow and Rao (1989), Post and van Vliet (2005), and Estrada (2002). Our hypothesis to be tested in this paper is whether the downside of cash-flow news is the risk factor that carries the highest and most consistent risk premium in the cross-section of stock returns. To develop and test this hypothesis, we combine the two different lines of literature by Campbell and Vuolteenaho (2004) and Ang et al. (2006). We develop a new, four-fold beta decomposition model. These betas measure the stock return's covariation with cash flow and discount rate news separately in both up and down markets.

Using our new decomposition method, we employ the CRSP universe to see how the four components of beta are priced in the cross-section of stock returns. We use Fama-MacBeth (1973) regressions with time varying betas to obtain risk premia estimates. We find that in the upside-downside beta model mainly downside beta is priced. For the cash flow and discount rate beta model, both cash flow and discount rate betas are priced in the cross section. When combining these two model in our new four-beta decomposition, we find that both downside cash flow risk and downside discount rate risk are significantly priced and typically carry the largest premium. The upside pricing factors are less in magnitude or less robust.

We perform an extensive set of additional analyses to check the robustness of our results. We control for different sample periods and different exchanges. We also investigate the impact of different approaches for calculating news factors as the robustness of Campbell and Vuolteenaho’s results has been disputed by Chen and Zhao (2008). They argue that different ways of constructing the cash flow news factor may overthrow the standard result that the cash flow news carries the highest premium. We therefore follow the alternative construction methods of Chen and Zhao. For this we use quarterly data and compare three different methods of decomposition that use direct and indirect modeling both for cash flow and discount rate news. Although our empirical findings are partly affected by the method of decomposition, the downside cash flow as well as downside discount components still prove to be the major sources of stock risk premia.

We also show that the methodology used for the pricing regressions is crucial. The typical approach would construct portfolios of individual assets. The returns on the portfolios should be less subject to idiosyncratic risk and measurement error problems. However, if one only uses portfolio returns, we observe a too high multicollinearity in the cross-sectional pricing regressions to produce any meaningful results. Ang et al. (2008) argue that there can be an important efficiency loss if portfolios are used in pricing regressions. The efficiency loss may outweigh the advantages of reduced measurement error problems. To solve this problem, they propose to run the pricing regressions with individual assets. Our results show that if we adopt this approach, there is sufficient information to identify the relevant risk premia.

Finally, we extend our analysis to the economic significance of the premia captured by each of our four decomposed betas. We measure the economic impact by the product of the premium with the average beta of the assets under study. We compute this economic impact on the expected or average returns for each window of the Fama-Macbeth procedure. Our results show that although the overall premium for the downside cash flow beta is most robust in all our analyses, its contribution to the size of the overall risk premium is less substantial than that of the discount rate factors.

Many researchers have tried to improve upon the performance of the simple CAPM with the development of new asset pricing models. Some of these provide additional factors with a solid practical basis such as size, value, and momentum, see for example Fama and French (1993, 1996) and Carhart (1997). Others have introduced new pricing factors from a more theoretical perspective, such as liquidity (Pastor and Stambaugh (2003) and Amihud (2002)), preference-based factors (downside betas of Ang, Chen, and Xing (2006), co-skewness (Friend and Westerfield (1980) and Harvey and Siddique (2000)), or factors relating to deviations from market equilibrium (Lettau and Ludvigson (2001)). Rather than creating yet another new pricing model, this paper takes a different route and combines two perspectives in the asset pricing literature.

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 and provides some useful summary statistics. Section 4 presents and discusses the main empirical results, section 5 covers our robustness analyses, and section 6 discusses the economic significance of our findings. Section 7 concludes.

II. Methodology

II.1 Downside and Upside Betas

The CAPM may not provide a convincing description of the risk premium due to its reliance on the assumption of mean-variance preferences for investors. There is sufficient evidence that mean-variance preferences provide an incorrect description of typical investor behavior, see for example Estrada (2002) and Post and van Vliet (2005). Investors typically assign greater importance to downside volatility than to upside volatility.

An alternative measure of risk that was proposed by Markowitz (1959) is semi-variance. The semi-variance measures only downside volatility and has several conceptual advantages over the variance as a measure of risk. It matches more closely how investors actually perceive risk in financial markets (Estrada, 2002). As a natural extension of the standard CAPM, one can use the semi-variance as a measure of risk. This leads to asset pricing models as introduced by Hogan and Warren (1974) and Bawa and Lindenberg (1977) and Harlow and Rao (1989). They use general lower partial moments as measures of risk in their specifications. In such a framework, it is not so much the symmetric covariation (beta) with the market that is priced, but rather the covariation in bear market conditions (downside beta).

Harlow and Rao (1989) use the expected market return to distinguish up and down markets and define their downside beta as

(1)
$$\beta_i^{(-)} = \frac{E[(R_i - \mu_i)(R_m - \mu_m) \mid R_m < \mu_m)]}{E[(R_m - \mu_m)^2 \mid R_m < \mu_m)]},$$

where R_i is the return on stock i, R_m is the return on the market portfolio, μ is the expected stock return, and μ_m is the expected market return. Similarly, the upside beta can be defined as

(2)
$$\beta_i^{(+)} = \frac{E[(R_i - \mu_i)(R_m - \mu_m) \mid R_m > \mu_m)]}{E[(R_m - \mu_m)^2 \mid R_m > \mu_m)]}.$$

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 of stock returns and find that risk premia mainly reflect the 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. show that downside risk is a risk attribute separate from other well-known risk premium determinants such as size, book to market, and momentum.

II.2 Cash Flow and Discount Rate Betas

Campbell and Vuolteenaho (2004) decompose the market return into two components: a cash flow and a discount rate component. The beta of a stock is decomposed analogously. Part of beta is due to covariation of the individual stock return with the market's discount rate factor. The other part is due to covariation with the market's cash flow factor. Campbell and Vuolteenaho label the former 'good' beta, and the latter 'bad' beta. The good beta is labeled 'good' because 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 offset 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 rather than with the discount rate factor. They also show that different loadings to cash flow and discount rate news may explain part of the size and value premium puzzles in asset pricing. The main reason is that growth stocks, with low average returns, have high betas for the market portfolio, but these betas are predominantly 'good' betas with low risk premia. Value stocks by contrast have high average returns, but have higher 'bad' betas than growth stock do. Similarly, small stocks also have considerably higher cash-flow betas than large stocks, which is in line with the higher average realized returns for these stocks.

We use a similar approach for calculating discount rate and cash flow betas as in Campbell and Vuolteenaho (2004), which are based on the return decomposition of the market portfolio in Campbell and Shiller (1988) and Campbell (1991). Campbell and Shiller (1988) use a log-linear approximation of the present value relation for stock prices that allows for time-varying discount rates. They obtain the return decomposition

(3) $$r_{t+1} - E_t r_{t+1} \approx (E_{t+1} - E_t)\sum_{i=0}^{\infty} \rho^i \Delta d_{t+1+i} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \equiv N_{CF,t+1} - N_{DR,t+1} ,$$

where r_t is the log stock 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 all information available at time *t*, and ρ is a parameter of linearization defined as $\rho \equiv 1/(1+\exp(\overline{d_t - p_t}))$. In our implementation later on we follow the earlier literature and assume an annual ρ of 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. The factor $N_{DR,t+1}$ 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, we can also define two separate betas. The cash-flow beta is given as

(4a) $$\beta_{i,CF} = \frac{Cov(R_{i,t}, N_{CF,t})}{Var(U_{mt})} ,$$

and the discount rate beta as

(4b) $$\beta_{i,DR} = \frac{Cov(R_{i,t}, -N_{DR,t})}{Var(U_{mt})} ,$$

where $U_{mt} = r_{m,t} - E_{t-1} r_{m,t} = N_{CF,t} - N_{DR,t}$ is the unexpected market return at time *t*.

The key step in operationalizing the approach of Campbell and Vuolteenaho (2004) is to postulate a model for predicting expected future returns. We follow Campbell and Vuolteenaho and assume that the data is generated by a first order vector autoregressive (VAR) model:

(5) $$z_{t+1} = a + \Gamma z_t + u_{t+1} ,$$
$$e1' z_{t+1} = r^e_{M,t+1} ,$$

where z_{t+1} is a *m* by 1 state vector with $r_{M,t+1}$ as its first element, *a* is a *m* by 1 vector of constants, Γ is a *m* by *m* matrix of coefficients, and u_{t+1} is a vector of random shocks. The first element of

u_{t+1} thus equals the unexpected return in time t+1. Given the model in (5), the discount-rate news factor follows naturally by recursively substituting the VAR equation. The cash-flow news can then be taken as the residual of the market return minus the discount rate factor. The resulting factors are defined as:

$$N_{DR,t+1} = (e1'\lambda)u_{t+1}, \qquad (6)$$
$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1},$$

where e1 denotes a vector with its first element equal to unity and the remaining elements equal to zero, and where $\lambda \equiv \rho\Gamma(I-\rho\Gamma)^{-1}$. Of course, this formulation also allows for higher-order VAR models via a simple redefinition of the state vector to include lagged values.[†]

II.3 The Four-Beta Model

The arguments to distinguish between upside and downside risk are equally applicable in a context where we disentangle risk into its cash flow and discount rate component. For this reason, we combine the previous two approaches in a new four-fold beta model. The aim of this combination is 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

$$\beta_{i,DCF} = \frac{E[(R_i - \mu_i)(N_{CF} - \mu_{N_{CF}})\ |U_m < 0)]}{E[(U_m)^2\,|U_m < 0)]}, \qquad (7a)$$

$$\beta_{i,DDR} = \frac{E[(R_i - \mu_i)(-N_{DR} - \mu_{-N_{DR}})\ |U_m < 0)]}{E[(U_m)^2\,|U_m < 0)]}, \qquad (7b)$$

$$\beta_{i,UCF} = \frac{E[(R_i - \mu_i)(N_{CF} - \mu_{N_{CF}})\ |U_m > 0)]}{E[(U_m)^2\,|U_m > 0)]}, \qquad (7c)$$

$$\beta_{i,UDR} = \frac{E[(R_i - \mu_i)(-N_{DR} - \mu_{-N_{DR}})\ |U_m > 0)]}{E[(U_m)^2\,|U_m > 0)]}, \qquad (7d)$$

[†] The VAR approach is the dominant method in the literature for return decompositions. Chen and Zhao (2008) claim that the results of this methodology are sensitive to the decision to forecast expected returns explicitly and treat cash flows as a residual. Campbell, Polk and Vuolteenaho (2009) provide some more justification for using VAR models in this context. In section 6, we provide an alternative method of return decomposition that uses direct cash flow modeling in order to check whether our results are affected by the method of decomposition.

where R_i denotes the return on stock *i*. N_{CF} denotes cash flow news, $-N_{DR}$ denotes discount rate news, and U_m denotes the unexpected return on the market portfolio.

II.4 Testing Factor Models

After calculating the four different betas for our test assets, we test how these betas could be priced in the cross-section of stock returns using cross-sectional regressions. In particular, we test the following four factor models

(8a) $$E[r_i^e] = \alpha_i + \lambda_m \hat{\beta}_{i,m} + e_i ,$$

(8b) $$E[r_i^e] = \alpha_i + \lambda_{dowm} \hat{\beta}_{i,dowm} + \lambda_{up} \hat{\beta}_{i,up} + e_i ,$$

(8c) $$E[r_i^e] = \alpha_i + \lambda_{CF} \hat{\beta}_{i,CF} + \lambda_{DR} \hat{\beta}_{i,DR} + e_i ,$$

(8d) $$E[r_i^e] = \alpha_i + \lambda_{DCF} \hat{\beta}_{i,DCF} + \lambda_{DDR} \hat{\beta}_{i,DDR} + \lambda_{UCF} \hat{\beta}_{i,UCF} + \lambda_{UDR} \hat{\beta}_{i,UDR} + e_i .$$

We perform both conditional and unconditional tests. In the unconditional tests, we estimate each beta for each asset using monthly returns over the complete sample period from July 1963 to December 2008. In the conditional tests, we use the Fama-MacBeth procedure with time-varying betas estimated over sixty month rolling windows. In this way, a time series of the risk premia corresponding to the time-varying betas can be computed. The test then considers the mean of the time series of risk premia. All tests focus on whether the risk premium is positive and significantly different from zero. To correct for possible autocorrelation in the time-varying risk premia, we use heteroskedasticity and autocorrelation consistent (HAC) standard errors in our conditional tests.

III. Data

In order to specify state variables that have predictive power on the value weighted excess market return we use in our VAR system the following variables: (i) the log excess market return defined as the log of the CRSP value weighted market index (from Kenneth French's website) minus the log of the three-month Treasury bill; (ii) the short-term interest rate, i.e. the three-month Treasury Bill rate from Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis; and (iii) the dividend yield on the S&P 500 composite price index calculated from data provided by Robert Shiller's website. Campbell and Vuolteenaho (2004) also stress the importance of the small stock value spread as an important element of the VAR model. We have also tried this variable in our model for our sample, but found that the variable is no longer significant over the whole updated sample.[‡]

The ability of the dividend yields for prediction of excess returns has been largely accepted and documented in the finance literature (see, e.g., Campbell (1991), Cochrane (1992, 2008) and Lettau and Ludvigson (2001)). Ang and Bekaert (2007) point out that the ability of the dividend yield to predict excess returns is best visible at shorter horizons by specifying the short-term interest rate as an additional regressor, although they express some doubts about the predictive power of dividend yields in the long-term. Table I shows the results of the VAR parameter estimates for the return decomposition.

[Insert Table I here]

We use monthly excess market returns from Kenneth French's data library and use the previously described VAR methodology to decompose the market return into cash flow (CF) news and discount rate (DR) news. The variance covariance matrix of news is presented in Table II. The variance of the DR news appears almost twice the size of the variance of CF news.

[Insert Table II here]

We use two different categories of data as base assets for testing our factor models: portfolios and individual stocks. For the portfolio approach, we use 25 Fama-French portfolios sorted on size and book-to-market value. We also investigate 40 additional portfolios sorted on past risk characteristics (downside beta, upside beta, cash-flow beta and discount rate beta). On the individual stock level we employ the whole universe of individual stocks traded on the NYSE, AMEX and NASDAQ over the whole sample period of July 1963 to December 2008, which have share codes 10 or 11 in the CRSP database. For robustness checks, we use these three exchanges separately to investigate the effect of different characteristics of assets in these exchanges on our empirical findings. For robustness checks of our results we also use the lower frequency of quarterly data of individual stocks as well as different sample periods.

IV. Empirical Results

[‡] We do confirm the significance over the earlier sample of Campbell and Vuolteenaho.

IV.1 Portfolios versus Individual Stocks

As our first base assets for testing the factor models in (8a-d), we used the 25 monthly Fama-French portfolios sorted on size and book-to-market value. However, it turns out that these aggregate portfolios result in too high a degree of multicollinearity between the different betas estimated to be useful to empirically identify the risk premia in the cross-sectional regressions of the Fama-MacBeth procedure.

To mitigate this problem, we augmented the set of test portfolios with 40 other test portfolios: ten portfolios sorted on 60-month rolling window estimates of downside beta, upside beta, cash-flow beta, and discount rate beta, respectively. As expected, multicollinearity problems are reduced, but still present. For example, using these 65 portfolios the correlation between the estimated downside cash flow beta and the downside discount rate beta is 0.975, between the estimated downside cash flow beta and upside discount rate beta 0.951, and between the estimated downside discount rate beta and upside discount rate beta 0.959.

Also a second attempt to reduce the multicollinearity problem proved unsuccessful. Using a double-sorting procedure we form 25 portfolios double-sorted on DCF and DDR (first 5 portfolios sorted by DCF and then within each portfolios sorted 5 portfolios based on DDR) and another 25 portfolios double-sorted based on UCF and UDR. However, even by using these double-sorted portfolios, the multicollinearity problem remains too severe to produce useful estimates of risk premia.

Our findings thus far are a typical illustration of the analysis by Ang et al (2008). Using portfolios rather than individual stocks as test assets is a standard procedure in finance to mitigate the errors in variables problem in the cross-sectional Fama-MacBeth regressions due to the use of estimated rather than true betas. However, this comes at the expense of a reduced cross-sectional spread in the estimated betas and therefore a loss of efficiency. Ang et al. show analytically and empirically that the conclusions drawn on individual versus portfolio test assets can differ substantially because of this. They also indicate that the use of individual stocks as test assets permits more efficient tests of in asset pricing regressions. We follow their recommendation that when just two-pass cross-sectional regression coefficients are estimated, there should be no reason to create portfolios and the asset pricing tests should be better run on individual stocks. Compared to our previous analysis based on portfolios of stocks, we now obtain sufficient cross-sectional dispersion in the estimated four betas to run our pricing regressions in (8a-d).

IV.2 Baseline Results

For testing our factor models using individual stocks, we use the 60-month rolling window Fama-MacBeth procedure with time-varying betas. Stocks that are not observed over the complete 60-month window are deleted from the cross-sectional regression in that particular time step. For the remaining stocks, we regress the realized average excess returns over the 60-month window on the realized betas, so that we can get an estimated premium for each beta. Then we roll the window for one-month forward and repeat the whole procedure. In this way, we obtain a time-series of estimated risk premia for each beta. Finally, we test whether the means of these time series are positive and significantly different from zero using HAC standard errors (see Andrews (1991)).

By using individual stocks as our base assets, the problem of multicollinearity of the regressors mitigates significantly: the three highest average correlations in this case are correlation between DDR and UDR betas, between DCF and UDR betas and between DCF and DDR betas that are 0.544, 0.412 and 0.379, respectively. Furthermore the number of observations in the regressions is much higher, which helps to calculate more precise estimates of premia.

Table III presents the results of testing the factor models for our sample for all listed companies on the NYSE, AMEX and NASDAQ during the period from July 1963 to December 2008. The first window spans July 1963 to June 1968 and the last January 2004 to December 2008, so that we analyze in total 487 sixty-months overlapping windows. The number of stocks in the different cross-sectional regressions varies from 1,431 to 3,949 for the different periods.

[Insert Table III here]

The second column in Table III shows that the standard beta has a significant and positive premium. The third column shows our estimates of the downside-upside beta model. We can see that it is mostly downside beta that drives the stock returns, while the upside beta premium is not significant. Moreover, the average premium for downside beta is almost tenfold that for upside beta. Model III shows our findings of the cash flow/discount rate beta model. Both cash flow and discount rate betas appear to be significant. Comparing the discount rate premium with the cash flow one, the two premia are not statistically different. Model IV presents the results of our new four-beta model. The results show that only the DCF and DDR betas are significant and have positive premia. The UCF beta premium is not significant, while the UDR beta is significant but only at the 10 percent level. Table III also indicates that the premium estimated for DCF and DDR betas is about 6 times the premium estimated for UCF and UDR betas.

To provide a more in-depth analysis of these first findings, we re-estimate our models using four different subsamples: the 1970s, 1980s, 1990s, and the period from January 2000 onwards (indicated as the 2000s). Table IV shows the results of these tests.

[Insert Table IV here]

Table IV reveals that in the downside/upside beta model the downside beta premium is positive and significant in all sub-samples. Upside beta has a negative premium for the 1970s, 1980s and 1990s, although it is not significant for the 1970s and 1990s. These results are in line with Ang et al. (2006) who also find a negative and significant premium for upside beta. Table IV shows that the 2000s are exceptional in this respect. During this period, upside beta has a positive premium and is also significant.

Our empirical findings for the cash flow/discount rate beta model prove that both the cash flow and the discount rate news are significant and have a positive premium over all sub-samples. For our four-beta model, we see that only the DCF beta has a positive premium throughout all sub-samples. The DDR beta has a positive premium in the 1970s, 1980s and 1990s but a negative (insignificant) premium in 2000s. Considering the UCF beta and UDR beta, we obtain mixed evidence of positive and negative premia in different periods, although both are insignificant over the whole sample.

We conclude that our empirical findings show that both cash flow and discount rate news are priced in the cross-section of stock returns, but only premia for downside beta prove to be robustly significant. These two effects imply that both DCF and DDR betas are priced in the cross-section, while UCF beta and UDR betas are not priced. In the next section, we perform additional analyses to test the robustness of our conclusions.

V. Robustness Analysis

In this section we present 3robustness tests. As a first robustness test, we analyze the stocks listed on the NYSE, AMEX and NASDAQ separately. As for example the NYSE has a substantially different stock base than NASDAQ, we get a first impression of the impact of size and industry on the estimated risk premia. In a second analysis, we control for size effect on our results and test our factor models using five size sorted sub-samples. And as a third robustness test, we investigate the robustness of our results to the choice of decomposition method used to obtain cash-flow and discount-rate news factors. In the previous section we followed the approach by

Campbell and Vuolteenaho (2004) by directly modeling discount rate news and retrieving cash flow news as the residual component of realized returns. Here, following Chen and Zhao (2008) we test the validity of our results if we model cash flow and discount rate news both directly, or even model cash-flow news directly while obtaining discount rate news as the residual component.

V.1 Different Exchanges

Traditionally, the NYSE includes the strongly established corporations, including most of the blue chips and big companies. AMEX on the other hand includes many middle-segment companies, while the NASDAQ mostly includes the smaller tech and growth companies. Although in recent years this traditional division has faded, by analyzing our results separately for the three different exchanges, we get a first impression about the robustness of our baseline results. Table V presents our findings. Using the CRSP dataset, we start the AMEX and NYSE sample in July 1963. The data for NASDAQ start January 1973. To facilitate the comparison, we also include in the table the results of our earlier analysis based on all exchanges. The number of stocks in the cross-sectional regressions varies between 889 and 1,182 for the NYSE, 171 to 655 for AMEX, and 1,236 to 2,197 for the NASDAQ listed stocks.

[Insert Table V here]

Table V shows for the downside/upside beta model that the downside beta has a positive and significant premium over all exchanges. The upside beta has a positive and significant premium for NYSE, a low but significant premium for AMEX, and an insignificant premium for NASDAQ. We interpret this as a first indication that the premia for upside and downside risk may be correlated with the size effect. We control for this later. We also see that the relative size of the downside beta premium grows as we move from the NASDAQ to the AMEX and further to the NYSE. For the cash flow/discount rate beta model, we see that both the cash flow and discount rate betas have positive and significant premia for all three exchanges. For the four-beta model, only the DCF beta has a significant premium over all three exchanges. The DDR beta premium is highly significant for AMEX and NASDAQ, but not for the NYSE. Again we interpret that as an indication that it may be important to control for size effects in our analysis. The UCF beta premium is significant for the NYSE and AMEX, but not for the NASDAQ listed corporations. The UDR beta premium is significant for the NYSE and for the NASDAQ at 5 and 10 percent, respectively. The DCF beta also has a larger premium than the UCF beta over all sub-samples. After controlling for different exchanges, we see that only the DCF beta is robustly priced in the cross-section of stock returns.

V.2 Directly Controlling for Size Effects

To control for possible size effects, we test our factor models using five size-sorted sub-samples. At the beginning of each window of the Fama-MacBeth estimation procedure, we form five quintiles of market capitalization sorted samples. We again include all three exchanges. Table VI displays the results.

[Insert Table VI here]

There is a clear size effect on the estimated premia for the downside/upside beta model. For small companies, we observe an estimated premium of downside beta that is more than seven times the size of the upside beta premium. Both premia are significant. For large companies, on the other hand, only upside beta is priced and has a positive premium. It appears that the size of the upside beta premium is rather stable across size classes. The downside premium appears much more correlated with a small stock effect.

The relative importance of the estimated premia for both cash flow and discount rate beta are also affected by size, although not as sharp for downside and upside beta. For the upper size classes, cash flow beta has a larger premium than discount rate beta. For the lowest size class, however, the two premia are indistinguishable. Also the relative importance of the cashflow premium to the discount rate premium appears to grow with size. This appears in line with the findings of Campbell and Vuolteenaho (2004), who obtain in their sample that the cash-flow and discount-rate beta differences alone between small and large companies can only explain *part of* the size premium effect.

For our four-beta model, the effect of size on the estimated premia confirms the general results for the downside/upside beta model as well as for the cash flow/discount rate beta model. For small companies, the DCF and DDR betas have almost equal average premia but much larger than (about four times) the average premia for UCF and UDR betas. For big companies, both UCF (with the largest average premium) and UDR beta premia are significant at the one percent level. The DCF beta premium is significant only at 10 percent, while the DDR beta premium is not significant. The premium for UDR is rather stable across size classes. The importance of the upside cash flow premium UCF, however, grows with size. This is suggestive of the downside risk notion being much more applicable if small companies are considered. If the well-established companies are considered, a much more symmetric notion of risk appears to apply.

V.3 Different Cash-Flow Discount-Rate Decompositions

In the return decompositions in the previous sections, we computed discount rate (DR) news (as the change in the discounted sum of future expected returns) directly, while we computed the cash flow (CF) news as the residual (unexpected market return minus the DR news). From Chen and Zhao (2008) it follows that one natural robustness check for our results is to model both CF and DR news directly in a VAR. Following this suggestion, we employ a VAR setting for predicting the dividend growth rate and calculate the discounted value of shocks to all future dividend growth rates of market portfolio as CF news on the market portfolio. Therefore, we decompose the unexpected dividend growth rate into CF news and a component that is not relevant for our current decomposition of returns. We use the lagged dividend growth rate and lagged market excess return as state variables. To reduce seasonality issues, we use quarterly rather than monthly data from 1953:Q2 to 2008:Q4 for calculating the divided growth rate. We estimate VAR coefficients as described in section II.2 and calculate CF news at time t+1 as

(9) $$N^{dir}{}_{CF,t+1} = e1' \, \lambda_2 \, v_{t+1},$$

where $\lambda_2 = (I - \rho \, \Gamma)^{-1}$ and Γ is the coefficient matrix, v_{t+1} is the residual vector at time t+1, while the variable in the first row of this vector is the unexpected dividend growth. The correlation between the direct CF news calculated by this method (9) and indirect CF news calculated by the method used in the previous section equals 0.286.

After calculating CF news by direct modeling, we test our factor models using two different ways of return decomposition. As a second decomposition method, we decompose unexpected market news to the three components as follows:

(10) $$U_{t+1} = N^{dir}_{CF,t+1} - N_{DR,t+1} + \text{noise},$$

where $N_{DR,t+1}$ is the DR news from the return decomposition calculated in our previous decomposition method. Thus, here we use direct modeling for both CF and DR news and the noise is part of the unexpected market return not captured by CF and DR news.

As a third decomposition method and similar to the first decomposition method, we decompose unexpected market news into two parts, but compute CF news directly and DR news (indirectly) as the residual. Thus, we have

(11) $$U_{t+1} = N^{dir}_{CF,t+1} - N^{res}_{DR,t+1},$$

so that $N^{res}_{DR,t+1} = U_{t+1} - N^{dir}_{CF,t+1}$.

The correlation between the indirect DR news calculated by (11) and direct DR news calculated by first decomposition method, equals 0.625.

Table VII shows the estimation results of testing the factor models using our three methods of return decomposition. We use a 40 quarters (120-months) rolling window to estimate betas and calculating average returns, resulting in 120-months overlapping windows in the sample. The number of stocks in each cross-sectional regression varies from 1,158 to 2,678 for stocks if we include all exchanges, and 771 to 948 for the NYSE subsample.

[Insert Table VII here]

For the cash flow/discount rate beta model we can see a clear effect of the three different methods of decomposition. For the NYSE sample, the CF beta premium is significant only for the first method of decomposition (direct discount rate modeling). It also has a positive premium for the second and third method of decomposition, but the premium is substantially lower and insignificant. The discount rate beta has a significant premium for all decomposition methods. Also its size remains stable. For the sample of all exchanges, both the CF beta premium and discount rate beta premium are significant. Part of this is driven by the effect that the downside risk premium is much more prevalent for small stocks, as shown earlier.

For our four-beta model, we can see that the DCF beta, DDR beta and UDR beta always have positive and significant premia irrespective of the chosen decomposition method. The UCF beta is both for NYSE listed and all exchanges listed companies not significant for the second and third decomposition method. The estimates of the downside risk premia appear to (substantially) increase if we switch from the first decomposition method to method II or III. This therefore reinforces our conclusion the price impact of downside risk: downside cash flow risk appears to be higher and more robustly priced than upside cash flow risk. Discount rate risk on the other hand appears more symmetrically priced for larger companies, while downside discount rate risk is priced higher if we also include small cap stocks in our sample (see the All Exchanges results).

Overall, we conclude that in all tests the DCF beta is the only part of beta that robustly has a positive and significant premium over all periods, samples, and decomposition methods. The DDR beta premium is also mostly significant, though not for NYSE listed stocks and not if we focus on the 2000s. We results on the premia for upside risk (UCF, UDR) are much more mixed and therefore less robust.

VI. Economic Significance

The investigation of estimated beta premia and the statistical significance are important for understanding whether different kind of betas is priced in the cross-section of stock returns. But considering that the magnitude of estimated beta premia are different among different models, it might well be the case that the economic significance of the overall premium could be different from the statistical significance or at least that the order of magnitude might change.

In order to provide more insight on the overall premium loaded by each beta, we calculate the overall premium for each beta by multiplying the estimated premium for each beta by the mean of beta in the cross-section. We then calculate the overall premium for each window following the Fama-MacBeth procedure, so that a time series of overall premia for each beta is calculated. Finally, we can test if the mean of each time series is positive and significantly different from zero.

Table VIII shows the overall premium loaded by each beta for all listed companies on the NYSE, AMEX and NASDAQ during our sample period July 1963 to December 2008 (546 months). This table is the counterpart to Table IV but here we calculate the overall premium for each beta. The bold figures in the table are the mean of the overall premium estimated for each beta with HAC standard errors in parentheses.

[Insert Table VIII here]

For the downside/upside beta model, the overall premium for downside beta is positive and significant in all sub-samples. The overall premium of upside beta is significant and negative for the 1980s and significant and positive in the 2000s, but not significant in the 1970s and 1990s and also not in the whole sample period. Comparing the size of the overall premium for downside and upside beta, we see that it is mainly downside beta that captures the systematic risk and upside beta only has a minor effect. For the cash flow/discount rate beta model, the overall premium for CF and DR betas is positive and significant in all sub-samples.

For our four-beta model, the overall premium for the DCF beta is positive and significant in all sub-samples. The DDR beta has a positive overall premium in the 1970s, 1980s and 1990 and also for the whole sample period but a negative (insignificant) overall premium in the 2000s. For both the UCF and UDR betas, we find mixed evidence of positive and negative overall premia in different periods, while both are insignificant over the whole sample.

For the NASDAQ and AMEX exchanges we find similar results to the investigation of all exchanges. As another test, we separately provide the results of calculating overall premia for

NYSE listed corporations. Table IX shows the overall premium loaded by each beta using NYSE stocks. We use the same procedure as for producing the results in Table VIII. The number of stocks in each regression varies from 889 to 1,182 stocks for the different time intervals.

[Insert Table IX here]

Table IX shows that for the downside/upside beta model, the downside beta has a positive and significant overall premium in the 1970s, 1980s and 1990s. We can report that upside beta has a positive and significant overall premium for the 1980s, 1990s and 2000s, and a negative overall premium for the 1970s. Thus, both downside and upside betas carries part of the overall premium for NYSE stocks. For the cash flow/discount rate beta model, we see that the overall premium for CF beta is significant in the 1980s and 1990s, while the overall premium for the DR beta is only significant in the 2000s. Exploring the results for the whole period, both CF and DR betas carries part of the premium in the cross-section. For our four-beta model, both the DCF and UCF beta have positive and significant overall premia throughout most of the sub-samples as well as over the whole sample period. We find mixed evidence on the overall premia for DDR and UDR betas but both are not significant over the whole period.

For testing whether our findings are affected by the chosen method of return decomposition, we separately calculate the overall premium for the three methods of decomposition. Table X, as the counterpart to Table VII, presents the results of estimating the overall premium for each beta using quarterly data.

[Insert Table X here]

As the chosen method of decomposition does not the downside/upside beta model, we find the same results for three methods of decomposition. For the NYSE listed corporations, both the downside and upside betas have positive and significant overall premia, while the size of the estimated overall premia is almost equal. For all listed companies, both downside and upside betas have positive and significant overall premium, while the overall premium for downside beta is about two times larger than the overall premium for upside beta.

For the cash flow/discount rate beta model, we can see a substantial effect of the three chosen methods of decomposition. For NYSE listed corporations, the overall premium for the CF beta is significant only for the first method of decomposition (direct discount rate modeling) but the DR beta is significant throughout all three decomposition methods. For companies in all exchanges, both the CF and DR betas are significant, while the DR beta has a larger overall premium than the CF beta. Comparing the three method of decomposition, we see that our empirical findings are substantially affected by the method of decomposition that we used.

For our four-beta model, the DCF, DDR and UDR betas have positive and significant overall premia irrespective of the decomposition method chosen and throughout both samples. The overall premium for the UCF beta is not significant for the second decomposition method for the NYSE listed corporations and also not for the third decomposition method for all exchanges. In general we see that discount rate news captures more premia than cash flow news and that the DDR beta has the largest overall premium of all four beta components in most of the investigated sub-samples.

VII. Conclusion

Through a decomposition of simple beta into downside and upside betas and also into cash-flow and discount rate betas, we show that we can get a better understanding about economic sources of risk that justify differences in the risk premium of individual stocks. In the downside/upside beta model (Ang et al. (2006)), we see that relative importance of downside and upside beta depends on the size of the companies. For small companies mainly downside risk is priced and captures the bulk of the premium, while for big companies, upside beta is priced more in the cross-section of stock returns. For the cash flow/discount rate beta model, both cash flow and discount rate betas are priced in the cross-section but their relative importance is also affected by the decomposing method that we use. The combined effect of downside/upside and cash-flow/discount rate news has been tested in our novel four-beta model and confirms our empirical findings above. For small companies mainly DCF and DDR beta are priced but for big companies also UCF and UDR beta are priced. However, the only part that is priced robustly in all sub-samples and over all methods of decomposition is the DCF beta. Finally, testing the economic significance of the different components of risk premia, we find that in most of the sub-samples, the impact of discount rate news components is more important that their cash flow counterparts in deriving stock return premia.

References

Andrews, D., 1991, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, *Econometrica*, 59, 817-858.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross Section and Time Series Effects, *Journal of Financial Markets*, 5, 31–56.

Ang, A., and G. Bekaert, 2007, Stock Return Predictability: Is It There?, *Review of Financial Studies*, 20, 651-707.

Ang, A., J., Chen, and Y. Xing, 2006, Downside Risk, *Review of Financial Studies*, 19, 1191-1239.

Ang, A., J. Liu, and K. Schwarz, 2008, Using Stocks or Portfolios in Tests of Factor Models, Columbia University Working Paper, available at SSRN #1106463

Bawa, V., and E. Lindenberg, 1977, Capital Market Equilibrium in a Mean Lower Partial Moment Framework, *Journal of Financial Economics*, 5, 189-200.

Black, F., 1972, Capital Market Equilibrium with Restricted Borrowing, *Journal of Business*, 45, 444-454.

Campbell, J., 1991, A Variance Decomposition for Stock Returns, *Economic Journal*, 101, 157-179.

Campbell, J., C. Polk, and T. Vuolteenaho, 2009, Growth or Glamour?, Fundamentals and Systematic Risk in Stock Returns, forthcoming in *Review of Financial Studies.*

Campbell, J., and R. Shiller, 1988, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, *Review of Financial Studies*, 1, 195-228.

Campbell, J., and T. Vuolteenaho, 2004, Bad Beta, Good Beta, *American Economic Review*, 94, 1249-1275.

Carhart, M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52, 57-82.

Chen, L., and X. Zhao, 2008, Return Decomposition, forthcoming in *Review of Financial Studies*, also available at SSRN #762601

Cochrane, J., 1992, Explaining the Variance of Price-Dividend Ratios, *Review of Financial Studies*, 5, 243–80.

Cochrane, J., 2008, The Dog That Did Not Bark: A Defense of Return Predictability, *Review of Financial Studies*, 21, 1533-1575.

Estrada, J., 2002, Systematic Risk in Emerging Markets: D-CAPM, *Emerging Markets Review*, 3, 365-379.

Fama, E., and K. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance*, 47, 427-465.

Fama, E., and K. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3–56.

Fama, E., and K., French, 1996, Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance*, 51, 55–84.

Fama, E., and J. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81, 607-636.

Friend, I., and R. Westerfield, 1980, Co-Skewness and Capital Asset Pricing, *Journal of Finance*, 35, 897-913.

Harlow, W., and R. Rao, 1989, Asset Pricing in a Generalized Mean-Lower Partial Moment Framework: Theory and Evidence, *Journal of Financial and Quantitative Analysis*, 24, 285-311.

Harvey, C., and A., Siddique, 2000, Conditional Skewness in Asset Pricing Tests, *Journal of Finance*, 55, 1263-1295.

Hogan, W., and J. Warren, 1974, Toward the Development of an Equilibrium Capital-Market Model Based on Semivariance, *Journal of Financial and Quantitative Analysis*, 9, 1-11.

Lettau, M., and S. Ludvigson, 2001, Consumption, Aggregate Wealth and Expected Stock Returns, *Journal of Finance*, 56, 815–849.

Lintner, J., 1965, The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics*, 47, 13-37.

Liu, N., and L. Zhang, 2008, Is the Value Spread a Useful Predictor of Returns?, *Journal of Financial Markets*, 11, 199–227.

Markowitz, H., 1959, *Portfolio Selection*, Yale University Press, New Haven, CT.

Pastor, L., and R. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy*, 111, 642–685.

Post, T., and P. van Vliet, 2005, Empirical Tests of the Mean-semi Variance CAPM, Working Paper, available at SSRN #557220.

Sharpe, W.F., 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance,* 19, 425-442.

Table I.

VAR Parameter Estimates for Return Decomposition

Notes: This table shows the OLS estimates of the vector autoregressive (VAR) model. Standard errors are given in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

	Intercept	$R^e_{m,t}$	SR_t	DY_t	R^2 %	***F***
$R^e_{m,t+1}$	-0.004	0.089**	-0.199***	0.539***	3.04	6.941
	(-0.005)	(0.038)	(0.067)	(0.162)		
SR_{t+1}	0.001	0.007*	0.992***	-0.012	97.5	8.63×10^3
	(0.001)	(0.004)	(0.007)	(0.017)		
DY_{t+1}	0.000*	-0.015***	0.004***	0.987***	99.16	2.62×10^4
	(0.000)	(0.001)	(0.002)	(0.004)		

Table II

Variance-Covariance Matrix of Market Index News

Notes: This table shows the variance covariance matrix of the unexpected market return and its two components, i.e. cash flow news and discount rate news, using a three-variable VAR model for decomposing the unexpected market return. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

	U	**CF**	**DR**
U	0.0018	0.0006	0.0012
CF	0.0006	0.0007	-0.0001
DR	0.0012	-0.0001	0.0013
Mean	0.0013	0.0082	-0.0069

Table III
Test of Factor Models Using Fama-MacBeth

Notes: This table shows the results of testing factor models using the Fama-MacBeth procedure with time varying betas and a sixty-months rolling window for estimating betas. Our sample includes monthly returns for all listed companies on the NYSE, AMEX and NASDAQ exchanges during the period from July 1963 to December 2008 (546 months), using the CRSP dataset. There are 487 sixty-months overlapping estimation windows in the sample. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 1,431 to 3,949 stocks in different periods. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

Model	**I**	**II**	**III**	**VI**
Intercept	0.408***	0.347***	0.410***	0.349***
	(0.063)	(0.063)	(0.062)	(0.062)
Beta	0.530***			
	(0.055)			
D Beta		0.513***		
		(0.048)		
U Beta		0.047*		
		(0.026)		
CF Beta			0.494***	
			(0.058)	
DR Beta			0.536***	
			(0.077)	
DCF Beta				0.475***
				(0.068)
DDR Beta				0.435***
				(0.068)
UCF Beta				0.075
				(0.058)
UDR Beta				0.075*
				(0.039)

Table IV
Test of Factor Models in Sub-sample Periods

Notes: This table shows the results of testing factor models using the Fama-MacBeth procedure with time varying betas and a sixty-months rolling window for estimating betas. Our sample includes monthly returns for all listed companies on the NYSE, AMEX and NASDAQ exchanges during the period from July 1963 to December 2008 (546 months), using the CRSP dataset. There are 487 sixty-months overlapping estimation windows in the sample. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 1,431 to 3,949 stocks in different periods. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

Period	1970s	1980s	1990s	200001-200812	196806-200812
Intercept	0.043	0.358***	0.614***	0.695***	0.408***
	(0.075)	(0.064)	(0.140)	(0.130)	(0.063)
Beta	0.272**	0.639***	0.426***	0.707***	0.530***
	(0.110)	(0.090)	(0.059)	(0.113)	(0.055)
Intercept	0.018	0.242***	0.525***	0.687***	0.347***
	(0.072)	(0.068)	(0.137)	(0.129)	(0.063)
D Beta	0.327***	0.741***	0.483***	0.425***	0.513***
	(0.114)	(0.082)	(0.040)	(0.081)	(0.048)
U Beta	-0.034	-0.061***	-0.008	0.288***	0.047*
	(0.043)	(0.019)	(0.040)	(0.053)	(0.026)
Intercept	0.030	0.389***	0.602***	0.697***	0.410***
	(0.073)	(0.059)	(0.139)	(0.127)	(0.062)
CF Beta	0.260***	0.477***	0.700***	0.685***	0.494***
	(0.089)	(0.068)	(0.129)	(0.089)	(0.058)
DR Beta	0.303**	0.669***	0.281***	0.751***	0.536***
	(0.154)	(0.116)	(0.061)	(0.180)	(0.077)
Intercept	-0.007	0.304***	0.508***	0.682***	0.349***
	(0.072)	(0.062)	(0.134)	(0.131)	(0.062)
DCF Beta	0.200**	0.745***	0.176*	0.907***	0.475***
	(0.097)	(0.066)	(0.100)	(0.156)	(0.068)
DDR Beta	0.421***	0.647***	0.626***	-0.149	0.435***
	(0.133)	(0.075)	(0.097)	(0.114)	(0.068)
UCF Beta	0.169	-0.142***	0.220***	0.122***	0.075
	(0.187)	(0.054)	(0.065)	(0.038)	(0.058)
UDR Beta	-0.079	0.005	-0.090**	0.452***	0.075*
	(0.048)	(0.032)	(0.035)	(0.098)	(0.039)

Table V
Test of Factor Models in Separate Exchanges

Notes: This table shows the results of testing factor models using the Fama-MacBeth procedure with time varying betas and a sixty-months rolling window for estimating betas. Our sample includes monthly returns for all listed companies on the NYSE, AMEX and NASDAQ exchanges during the period from July 1963 to December 2008 (546 months), using the CRSP dataset. There are 487 sixty-months overlapping estimation windows in the sample. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 1,431 to 3,949 stocks when we use all listed companies in the three exchanges together, and is in between 889 to 1,182 for the NYSE, 171 to 655 for the AMEX, and 1,236 to 2,197 for the NASDAQ, when we use them separately. The data for NASDAQ start from January 1973. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

Exchange	NYSE	Amex	Nasdaq	All Exchanges
Intercept	0.398***	0.385***	0.649***	0.408***
	(0.052)	(0.073)	(0.081)	(0.063)
Beta	0.324***	0.526***	0.616***	0.530***
	(0.055)	(0.049)	(0.055)	(0.055)
Intercept	0.392***	0.293***	0.542***	0.347***
	(0.052)	(0.072)	(0.084)	(0.063)
D_Beta	0.188***	0.488***	0.639***	0.513***
	(0.054)	(0.047)	(0.048)	(0.048)
U_Beta	0.146***	0.082**	0.025	0.047*
	(0.038)	(0.038)	(0.026)	(0.026)
Intercept	0.411***	0.377***	0.643***	0.410***
	(0.050)	(0.070)	(0.080)	(0.062)
CF_Beta	0.466***	0.627***	0.563***	0.494***
	(0.072)	(0.086)	(0.068)	(0.058)
DR_Beta	0.307***	0.465***	0.626***	0.536***
	(0.090)	(0.074)	(0.075)	(0.077)
Intercept	0.415***	0.285***	0.530***	0.349***
	(0.052)	(0.070)	(0.083)	(0.062)
DCF_Beta	0.374***	0.424***	0.555***	0.475***
	(0.080)	(0.071)	(0.084)	(0.068)
DDR_Beta	0.095	0.526***	0.565***	0.435***
	(0.081)	(0.082)	(0.069)	(0.068)
UCF_Beta	0.246***	0.153***	-0.017	0.075
	(0.070)	(0.057)	(0.043)	(0.058)
UDR_Beta	0.136**	0.055	0.071*	0.075*
	(0.055)	(0.050)	(0.038)	(0.039)

Table VI
Test of Factor Models using different Size Categories

Notes: This table shows the results of testing factor models using the Fama-MacBeth procedure with time varying betas and a sixty-months rolling window for estimating betas. Our sample includes monthly returns for all listed companies on the NYSE, AMEX and NASDAQ exchanges during the period from July 1963 to December 2008 (546 months), using the CRSP dataset. There are 487 sixty-months overlapping estimation windows in the sample. We deleted the stocks that have missing data in each window. In each window, we sort all companies based on the size of them in the beginning of the period and based on this sort divided them to 5 size categories. The number of stocks in each regression varies from 1,431 to 3,949 stocks in different periods. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

Size	Small	2	3	4	Big
Intercept	0.773***	0.330***	0.341***	0.428***	0.461***
	(0.110)	(0.073)	(0.061)	(0.050)	(0.053)
Beta	0.851***	0.659***	0.485***	0.302***	0.162***
	(0.049)	(0.051)	(0.060)	(0.061)	(0.062)
Intercept	0.634***	0.275***	0.344***	0.449***	0.467***
	(0.108)	(0.074)	(0.061)	(0.049)	(0.053)
D_Beta	0.791***	0.502***	0.344***	0.114**	-0.009
	(0.053)	(0.042)	(0.039)	(0.050)	(0.048)
U_Beta	0.115***	0.190***	0.152***	0.178***	0.164***
	(0.025)	(0.029)	(0.050)	(0.052)	(0.047)
Intercept	0.744***	0.328***	0.353***	0.443***	0.468***
	(0.109)	(0.072)	(0.061	(0.048)	(0.049)
CF_Beta	0.831***	0.768***	0.623***	0.405***	0.351***
	(0.074)	(0.054)	(0.070	(0.066)	(0.100)
DR_Beta	0.834***	0.676***	0.497***	0.363***	0.198*
	(0.048)	(0.077)	(0.092	(0.103)	(0.108)
Intercept	0.598***	0.269***	0.355***	0.461***	0.491***
	(0.105)	(0.074)	(0.061	(0.048)	(0.049)
DCF_Beta	0.659***	0.549***	0.502***	0.236***	0.154*
	(0.094)	(0.063)	(0.060	(0.068)	(0.093)
DDR_Beta	0.755***	0.429***	0.280***	0.098	-0.021
	(0.067)	(0.059)	(0.051	(0.068)	(0.100)
UCF_Beta	0.150***	0.296***	0.283***	0.336***	0.378***
	(0.048)	(0.046)	(0.058	(0.062)	(0.082)
UDR_Beta	0.135***	0.206***	0.140***	0.162**	0.125*
	(0.028)	(0.044)	(0.067	(0.072	(0.067)

Table VII

The Estimated Premium Using Quarterly Data and 3 Decompostion Methods

Notes: This table shows the results of testing factor models using the Fama-MacBeth procedure with time varying betas. Our main sample includes quarterly return for all listed companies on the NYSE, AMEX and NASDAQ exchanges during July 1963 to December 2008 (182 quarters), using the CRSP dataset. We use a 120 months (40 quarters) rolling window for estimating betas and average returns and there are 143 120-months overlapping windows in the sample. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 1,158 to 2,678 for stocks in all exchanges and 771 to 948 for stocks listed on the NYSE for different sample periods. For each sample, we use three different methods of decomposing the quarterly market returns: i) direct discount rate news modeling and indirect cash flow news modeling; ii) direct discount rate modeling and direct cash flow news modeling; and iii) indirect discount rate modeling and direct cash flow news modeling. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

	NYSE			**All Exchanges**		
Method	**I**	**II**	**III**	**I**	**II**	**III**
Intercept	0.955***	1.265***	0.962***	0.902***	1.359***	0.944***
	(0.164)	(0.185)	(0.159)	(0.191)	(0.217)	(0.188)
CF Beta	1.806***	0.814	0.693	2.202***	1.166**	1.179***
	(0.238)	(0.695)	(0.595)	(0.191)	(0.530)	(0.405)
DR Beta	1.169***	1.389***	1.338***	1.725***	1.916***	1.813***
	(0.124)	(0.149)	(0.107)	(0.092)	(0.125)	(0.096)
Intercept	0.986***	1.112***	0.952***	0.842***	1.210***	0.868***
	(0.157)	(0.180)	(0.158)	(0.198)	(0.220)	(0.197)
DCF Beta	0.437***	3.426***	2.242***	1.827***	3.489***	2.476***
	(0.170)	(0.698)	(0.681)	(0.185)	(0.527)	(0.510)
DDR Beta	0.655***	1.145***	0.688***	1.026***	1.317***	1.266***
	(0.112)	(0.124)	(0.123)	(0.096)	(0.129)	(0.100)
UCF Beta	1.215***	-0.510	-0.069	0.795***	-0.095	0.102
	(0.223)	(0.401)	(0.376)	(0.156)	(0.278)	(0.237)
UDR Beta	0.547***	0.309**	0.619***	0.632***	0.613***	0.582***
	(0.106)	(0.122)	(0.111)	(0.082)	(0.093)	(0.096)

Table VIII

Overall Premium for Different Decades Using Monthly Data from all Exchanges

Notes: This table shows the overall premium loading for each beta calculated by multiplying the average betas by the estimated premium in each window in the Fama-MacBeth procedure and calculating the average of the overall premium. We use a sixty-months rolling window for estimating betas. Our main sample includes monthly return for all listed companies on the NYSE, AMEX and NASDAQ during July 1963 to December 2008 (546 months), using the CRSP database. There are 487 sixty-months overlapping windows in the main sample. Sub-samples are the decades 1970s, 1980s, 1990s and the period from January 2000 to December 2008, and include the windows ending in these periods. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 1,431 to 3,949 stocks in different periods. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

Period	1970s	1980s	1990s	200001-200812	196806-200812
Intercept	0.043	0.358***	0.614***	0.695***	0.408***
	(0.075)	(0.064)	(0.140)	(0.130)	(0.063)
Beta	0.337**	0.702***	0.395***	0.661***	0.558***
	(0.141)	(0.103)	(0.056)	(0.098)	(0.061)
Intercept	0.018	0.242***	0.525***	0.687***	0.347***
	(0.072)	(0.068)	(0.137)	(0.129)	(0.063)
D_Beta	0.414***	0.876***	0.484***	0.415***	0.578***
	(0.143)	(0.105)	(0.044)	(0.076)	(0.059)
U_Beta	-0.052	-0.059***	0.001	0.254***	0.041
	(0.056)	(0.018)	(0.031)	(0.047)	(0.026)
Intercept	0.030	0.389***	0.602***	0.697***	0.410***
	(0.073)	(0.059)	(0.139)	(0.127)	(0.062)
CF_Beta	0.078**	0.119***	0.252***	0.382***	0.193***
	(0.038)	(0.020)	(0.045)	(0.047)	(0.025)
DR_Beta	0.272**	0.551***	0.156***	0.277***	0.363***
	(0.130)	(0.092)	(0.030)	(0.065)	(0.056)
Intercept	-0.007	0.304***	0.508***	0.682***	0.349***
	(0.072)	(0.062)	(0.134)	(0.131)	(0.062)
DCF_Beta	0.079*	0.218***	0.087**	0.523***	0.212***
	(0.043)	(0.041)	(0.037)	(0.081)	(0.034)
DDR_Beta	0.343***	0.561***	0.396***	-0.075	0.353***
	(0.105)	(0.060)	(0.062)	(0.048)	(0.050)
UCF_Beta	0.034	-0.023**	0.064***	0.062***	0.028
	(0.064)	(0.010)	(0.018)	(0.021)	(0.019)
UDR_Beta	-0.070	-0.001	-0.045***	0.164***	0.023
	(0.047)	(0.026)	(0.015)	(0.034)	(0.021)

Table IX
The Overall Premium in Different Decades Using NYSE stocks

Notes: This table shows the overall premium loading for each beta calculated by multiplying the average betas by the estimated premium in each window in the Fama-MacBeth procedure and calculating the average of the overall premium. We use a sixty-months rolling window for estimating betas. Our main sample includes monthly return for all listed companies on the NYSE during July 1963 to December 2008 (546 months), using the CRSP database. There are 487 sixty-months overlapping windows in the main sample. Sub-samples are the decades 1970s, 1980s, 1990s and the period from January 2000 to December 2008, and include the window endings in these periods. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 889 to 1,182 stocks in different periods. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

Period	**1970s**	**1980s**	**1990s**	**2000s**	**196806-200812**
Intercept	0.208***	0.442***	0.407***	0.663***	0.398***
	(0.065)	(0.135)	(0.031)	(0.089)	(0.052)
Beta	0.085	0.440***	0.348***	0.266***	0.325***
	(0.132)	(0.148)	(0.044)	(0.053)	(0.062)
Intercept	0.201***	0.448***	0.392***	0.665***	0.392***
	(0.065)	(0.138)	(0.024)	(0.087)	(0.052)
D_Beta	0.282***	0.298**	0.189**	-0.077	0.224***
	(0.091)	(0.140)	(0.081)	(0.063)	(0.059)
U_Beta	-0.190**	0.137***	0.173***	0.341***	0.108***
	(0.080)	(0.047)	(0.045)	(0.057)	(0.037)
Intercept	0.189***	0.472***	0.432***	0.670***	0.411***
	(0.063)	(0.128)	(0.030)	(0.089)	(0.050)
CF_Beta	0.050	0.227***	0.353***	0.016	0.155***
	(0.040)	(0.032)	(0.031)	(0.054)	(0.026)
DR_Beta	0.054	0.183	-0.030	0.244***	0.158***
	(0.122)	(0.131)	(0.038)	(0.059)	(0.059)
Intercept	0.162**	0.518***	0.430***	0.682***	0.415***
	(0.065)	(0.130)	(0.023)	(0.088)	(0.052)
DCF_Beta	0.046	0.221***	0.126*	0.167*	0.136***
	(0.030)	(0.039)	(0.065)	(0.093)	(0.032)
DDR_Beta	0.251***	0.010	0.031	-0.180***	0.080
	(0.070)	(0.107)	(0.061)	(0.064)	(0.051)
UCF_Beta	0.049	0.051**	0.166***	0.033	0.068***
	(0.064)	(0.022)	(0.030)	(0.031)	(0.022)
UDR_Beta	-0.216***	0.082*	0.002	0.227***	0.026
	(0.071)	(0.043)	(0.020)	(0.040)	(0.031)

Table X
Overall Premium for Quarterly Data and 3 Decomposition Methods

Notes: This table shows the overall premium loading for each beta calculated by multiplying the average betas by the estimated premium in each window following the Fama-MacBeth procedure and calculating the average of the overall premium. Our main sample includes quarterly return for all listed companies on the NYSE, AMEX and NASDAQ during July 1963 to December 2008 (182 quarters), using the CRSP database. We use a 120-months (40 quarters) rolling window for estimating betas and there are 143 120-months overlapping windows in the sample. We deleted the stocks that have missing data in each window. The number of stocks in each regression varies from 1,158 to 2,678 for stocks on all exchanges and 771 to 948 for stocks in NYSE in different periods. For each sample, we use three different methods of decomposing the quarterly market returns: i) direct discount rate news modeling and indirect cash flow news modeling; ii) direct discount rate modeling and direct cash flow news modeling; and iii) indirect discount rate modeling and direct cash flow news modeling. The table shows the mean of the premium estimated for each beta and the corresponding HAC standard errors in parentheses. ***, **, * denotes significance at the 1, 5, and 10 percent level, respectively.

	NYSE			All Exchanges		
Method	**I**	**II**	**III**	**I**	**II**	**III**
Intercept	0.971***	0.971***	0.971***	0.933***	0.933***	0.933***
	(0.159)	(0.159)	(0.159)	(0.188)	(0.188)	(0.188)
Beta	1.344***	1.344***	1.344***	2.058***	2.058***	2.058***
	(0.115)	(0.115)	(0.115)	(0.110)	(0.110)	(0.110)
Intercept	0.994***	0.994***	0.994***	0.875***	0.875***	0.875***
	(0.153)	(0.153)	(0.153)	(0.195)	(0.195)	(0.195)
D Beta	0.674***	0.674***	0.674***	1.412***	1.412***	1.412***
	(0.081)	(0.081)	(0.081)	(0.095)	(0.095)	(0.095)
U Beta	0.647***	0.647***	0.647***	0.705***	0.705***	0.705***
	(0.122)	(0.122)	(0.122)	(0.109)	(0.109)	(0.109)
Intercept	0.955***	1.265***	0.962***	0.902***	1.359***	0.944***
	(0.164)	(0.185)	(0.159)	(0.191)	(0.217)	(0.188)
CF Beta	0.507***	0.079	0.058	0.678***	0.101**	0.074**
	(0.081)	(0.049)	(0.039)	(0.072)	(0.041)	(0.029)
DR Beta	0.853***	0.970***	1.295***	1.412***	1.531***	1.973***
	(0.102)	(0.095)	(0.101)	(0.082)	(0.086)	(0.100)
Intercept	0.986***	1.112***	0.952***	0.842***	1.210***	0.868***
	(0.157)	(0.180)	(0.158)	(0.198)	(0.220)	(0.197)
DCF Beta	0.141***	0.227***	0.142***	0.605***	0.237***	0.146***
	(0.049)	(0.057)	(0.049)	(0.064)	(0.048)	(0.036)
DDR Beta	0.460***	0.784***	0.611***	0.813***	1.010***	1.323***
	(0.074)	(0.083)	(0.111)	(0.085)	(0.098)	(0.113)
UCF Beta	0.297***	-0.013	-0.034*	0.205***	0.033*	0.008
	(0.057)	(0.023)	(0.020)	(0.051)	(0.019)	(0.015)
UDR Beta	0.430***	0.204**	0.642***	0.527***	0.501***	0.647***
	(0.087)	(0.096)	(0.115)	(0.066)	(0.074)	(0.111)