Characterising the Asymmetric Dependence Premium

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Abstract

We examine the relative importance of asymmetric dependence (AD) and systematic risk in the cross-section of US equities. Using a β-invariant AD metric, we demonstrate a lower-tail dependence premium equivalent to 35% of the market risk premium, compared with an upper-tail dependence discount that is 41% of the market risk premium. Lower-tail dependence displays a constant price between 1989-2009, while the discount associated with upper-tail dependence appears to be increasing in recent years. Subsequently, we find that return changes in US equities between 2007-2009 reflected changes in systematic risk and upper-tail dependence. This suggests that both systematic risk and AD should be managed in order to reduce the return impact of market downturns. Our findings have substantial implications for the cost of capital, investor expectations, portfolio management and performance assessment.

Key words: Asymmetric dependence, asset pricing, tail risk, downside risk, β, J^{Adj}.

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Does the cross-section of stock returns reflect an premium for asymmetric dependence (AD) independently of linear market risk? Do changes in upper and lower tail dependence between stock returns and the market occur independently of fundamental shifts in systematic risk? Are the premia associated with upper and lower tail dependence equal and unchanging? The existence of an AD discount or premium, separate from the premium attached to linear dependence (β), will have significant impacts of the firms cost of capital and capital raising decisions. Furthermore, the existence of an AD premium also raises substantial questions about the ability of standard performance assessment metrics to identify appropriate risk-adjustments to apply to returns.

We identify the existence and nature of an AD premium by employing an adjusted version of the J-statistic (Hong, Tu, and Zhou, 2007) to capture the risk that a stock and the market jointly decline (appreciate) in excess of the joint return decline (appreciation) implied by ordinary market β. We then seperately control for Adjusted J and β in a regression on returns in order to assess the relative size of the AD risk premia and the market risk premia over time. We find that upper-tail (lower-tail) dependence attracts a significant discount (premium), that is robust to controlling for commonly cited return covariates.

The importance of AD in asset pricing has been well established in the literature from both a conceptual and empirical perspective. By combining the existence of state-dependent correlations with state-dependent investor preferences, we expect the downside risk associated with lower-tail dependence (LTD) to attract a premium in asset prices, whilst upside potential associated with upper-tail dependence (UTD) to yield a discount. Bali, Demirtas, and Levy (2009) demonstrate this using Value-at-Risk (VaR) and expected shortfall to demonstrate a significant relationship between downside risk and the returns of the NYSE/AMEX/NASDAQ value weighted index. Similarly. Post and van Vliet (2006) use a stochastic dominance framework to show that downside risk is important in explaining the high return of small, value and winner stocks, and Ang, Chen, and

Xing (2006) find that downside β attracts a premium of approximately 6% per annum.

It has been difficult to identify whether changes in traditional tail risk metrics, such as conditional upside and downside β and VaR, occur as a result of changes in the overall relationship between stock returns and the market, or as a result of changes in the sensitivity of stock returns to extreme market movements. The risk caused by upper and lower tail co-movements and the ability to differentiate these risks from ordinary co-movements is likely to have important implications for asset allocation decisions [1]. For example, an increase in CAPM β will also be reflected by an increase in both upside and downside β. In this instance, any downside risk hedge utilising changes in downside β is likely to be confounded as downside risk will generally be offset by upside risk in the long run. In general, the hedging demands of investors will differ for exposure to stocks that fall disproportionately with market downturns, relative to upturns (an increase in tail-risk), in contrast to stocks that are symmetric in their response to market movements (an increase in systematic risk). In a Merton (1973) style dynamic economy, this leads to expected stock returns that are linear functions of both market β and the sensitivity of a hedge portfolio, the latter of which will depend on the magnitude and symmetry of upside and downside responses to market returns.

The central question we address in this paper is whether upside and downside risk associated with AD attract a premium independent of the premium attached to β. To the best of our knowledge, the relative magnitude of the premia attached to dependence driven tail risk and ordinary market risk has yet to be established [2]. To highlight the importance

[1] A significant reduction in portfolio value can occur with moderate market declines if dependence is state-dependent, particularly if there is a tendency for dependence amongst assets to increase more during bear market periods relative to bull market periods. Dependence of this nature has been established between international equity indices and amongst subsets of the US equity market (Ang and Bekaert, 2002; Ang and Chen, 2002; Butler and Joaquin, 2002; Campbell, Koedijk, and Kofman, 2002; Erb, Harvey, and Viskanta, 1994; Hartmann, Straetmans, and de Vries, 2004; Hong, Tu, and Zhou, 2007; Longin and Solnik, 2001; Patton, 2004; Ramchand and Susmel, 1998) suggesting that state-dependence is non-diversifiable.

[2] Pedersen and Hwang (2007) show that the CAPM can be used to explain 50–80% of the returns of UK equities, while downside β explains only 15–25%. The authors therefore rule out the general applicability of downside β in explaining UK equity return variation on the basis of the proportion of equities explained by the CAPM and the lower-partial moment

of considering the systematic risk premium separate from the premia attached to AD, consider two assets, A and B, that have identical βs, equal average returns, and the same level of dependence in the lower tail. Furthermore, suppose B displays dependence in the upper tail that is equal in absolute magnitude to the level of dependence in the lower tail, but A has no dependence in the upper tail. In this example, B is symmetric (but not necessarily elliptical), whereas A is asymmetric displaying lower-tail dependence (see Figure 1). The return associated with an exposure to systematic risk should be the same for A and B because they have the same β. In addition, a rational, non-satiable investor that accounts for relative differences in upside and downside risk should prefer B over A because B is less likely to suffer from cumulative losses in the long run compared to A. A downside risk averse investor should also prefer B over A as the long term risk of loss is lower for B. These preferences should drive higher returns for assets that display LTD and lower returns for assets that display UTD, independent of the returns attached to β.

[Figure 1 about here]

Our main contribution to the existing literature is two-fold. Our first contribution lies in measuring AD over and above the tail dependence implied by β, rather than methodological improvements over previous studies in this area. We achieve this using an adjusted version of an existing asymmetry metric to build on the previous efforts of Ang, Chen, and Xing (2006). We do not dispute the existence of a downside risk premium nor the economic framework upon which the premium is built in the literature. Rather, we find that despite the statistical significance of LTD in explaining cross-sectional return variation, the magnitude of the associated downside risk premium is only 35% of the magnitude of the premium for traditional β. Furthermore, we find UTD attracts a discount, and represents 41% of the premium attached to β making it relatively more important than the downside risk associated with LTD in explaining equity return variation. These re-

asset pricing framework. They do not quantify the relative magnitude of the compensation for systematic and downside risk, however.

sults hold after controlling for book-to-market ratio, size, past return, idiosyncratic risk, coskewness and cokurtosis, and are tested for robustness by using alternative data length specifications and by analyzing whether past AD can predict future return.

Our second contribution involves an analysis of how the AD premia has changed over time relative to the premium for systematic risk. We find that the premium associated with LTD has been priced at a relatively constant level of 0.6% pa (per unit of downside risk loading) over the 20 years ranging between 1989 and 2009. Changes in AD therefore occur as a result of changes in the preference for stocks that display UTD with the market, or as a result of changes in the sensitivity of stock returns to upward market movements. In addition, the 2007-2009 financial crisis appears to be as much a systematic risk story as it is an AD story implying that the risks associated with both linear dependence and higher-order dependence should be managed to reduce the portfolio impact of future market crashes.

Our results therefore build on previous work by Ang, Chen, and Xing (2006) by showing that both linear dependence and higher-order dependencies are important in the cross-section. These results imply that important price information is contained within the relative magnitude of upside and downside risk as well as within the overall relationship between asset returns.

1 The Adjusted J Statistic

1.1 Capturing Asymmetric Dependence

We measure AD using an adjusted version of the J statistic, originally proposed by Hong, Tu, and Zhou (2007). J^{Adj} is a model free and β-invariant statistic that measures AD using conditional correlations across opposing sample exceedances. Several alternative metrics have been used to assess non-linearities in the dependence between asset returns, including downside Beta (Ang, Chen, and Xing, 2006), copula function parameters (see

Genest, Gendron, and Boureau-Brien, 2009), and the J-statistic itself. However these metrics have difficulty capturing the sensitivity of asset returns to AD independently of other price-sensitive factors such as the CAPM Beta, as they are not β-invariant.

[Figure 2 about here]

To illustrate this point, we simulate $N = 25000$ pairs of random variables (x, y) where $x_i \sim N(0.25, 0.15)$, and $y_i = \beta x_i + \epsilon_i$, where $\epsilon_i \sim N(0, (x_i + 0.25)^\alpha)$. When $\alpha = 0$, no AD is present, and (x, y) are bivariate normal with linear dependence equal to β. Higher LTD is proxied by increasing $\alpha > 0$, and higher UTD is proxied by decreasing $\alpha < 0$. OLS estimates of the CAPM Beta and downside Beta, IFM estimates[3] of the Clayton copula parameter of lower tail dependence are provided in Figure 2, for various combinations of α and β. The CAPM Beta and downside Beta are largely insensitive to AD and their estimates of linear dependence are not confounded by the presence of AD. The Clayton copula parameter is unable to uniquely identify either the presence or level of AD or of linear dependence. This seems to be due to the fact that the Clayton copula parameter attempts to fit both dimensions of dependence with a single parameter. As a result, the copula measure of AD is sensitive to the value of linear dependence and to the value of α. Almost all copula families, including multi-parameter families, will similarly be unable to determine AD separate from linear dependence unless one parameter is especially dedicated to estimating linear dependence. To the best of our knowledge, a copula with these characteristics is yet to be described in the literature.

[Figure 3 about here]

1.2 Adjusting the J-statistic

The J-statistic is able to identify AD and also provide critical values to establish a hypothesis test on the presence of AD. We introduce a β-invariant J statistic, in order

[3] For full details on the Inference Function for Margins (IFM) method of estimating copula parameters, see Joe (1997)

to establish the AD premium separately from the CAPM β premium while retaining the integrity of the dependence structure. We obtain β-invariance by unitizing β for each data set before a modified version of the J statistic is computed. In particular, given $\{R_{it}, R_{mt}\}_{t=1}^{T}$ (Figure 4(a)), we first let $\hat{R}_{it} = R_{it} - \beta R_{mt}$ (Figure 4(b)) where R_{it} and R_{mt} are the continuously compounded return on the i^{th} asset and the market respectively, and $\beta = \text{cov}(R_{it}, R_{mt})/\sigma^2_{R_{mt}}$. This initial transformation sets $\beta_{\hat{R}_{it},R_{mt}} = 0$ making it possible to standardize the data without contaminating the linear relationship between the variables (Figure 4(c)). Standardization yields R^S_{mt} and $\hat{R}^S_{it}$ and ensures that the standard deviation of the market model residuals, a measure of idiosyncratic risk, is identical for all data sets[4]. We then re-transform the data to have $\hat{\beta} = 1$ by letting $\tilde{R}_{mt} = R^S_{mt}$ and $\tilde{R}_{it} = \hat{R}^S_{it} + R^S_{mt}$ (Figure 4(d)). Therefore, all data display the same β after these transformations[5], forcing the output of J^{Adj} to be invariant to the overall level of linear dependence, as well as being independent to idiosyncratic risk. The β-invariance of J^{Adj} is demonstrated in Figure 3, calculated using the same simulations as in Section 1.1.

[Figure 4 about here]

J^{Adj} is given by:

$$J^{Adj} = \left[\text{sgn}\left(\left[\tilde{\rho}^+ - \tilde{\rho}^-\right]\mathbf{1}\right)\right] T \left(\tilde{\rho}^+ - \tilde{\rho}^-\right)' \tilde{\Omega}^{-1} \left(\tilde{\rho}^+ - \tilde{\rho}^-\right), \tag{1}$$

for $\tilde{\rho}^+ = \{\tilde{\rho}^+(\delta_1), \tilde{\rho}^+(\delta_2), \ldots, \tilde{\rho}^+(\delta_N)\}$ and $\tilde{\rho}^- = \{\tilde{\rho}^-(\delta_1), \tilde{\rho}^-(\delta_2), \ldots, \tilde{\rho}^-(\delta_N)\}$, where, $\mathbf{1}$ is an $N \times 1$ vector of ones, $\hat{\Omega}$ is an estimate of the the variance-covariance matrix (Hong,

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4 From the market model, total variance of a stock's returns can be written as $\sigma^2_T = \beta^2\sigma^2_M + \sigma^2_\epsilon$ where σ^2_M is the markets variance and σ^2_ϵ is the variance of the idiosyncratic component of returns. Since we set $\beta = 0$, $\sigma^2_T = \sigma^2_\epsilon$. Hence, standardizing at this point is equivalent to dividing out the idiosyncratic component of transformed returns.

5 At this point, $\tilde{R}_{mt} \sim N(0, 1)$ whereas $\tilde{R}_{it} \sim N(0, \sqrt{2})$ assuming marginal distributions are normal. This holds for all data sets.

Tu, and Zhou, 2007) for the difference vector $(\tilde{\rho}^{+} - \tilde{\rho}^{-})$ and:

$$\tilde{\rho}^{+}(\delta) = \text{corr}\left(\tilde{R}_{mt}, \tilde{R}_{it} | \tilde{R}_{mt} > \delta, \tilde{R}_{it} > \delta\right) \tag{2}$$

$$\tilde{\rho}^{-}(\delta) = \text{corr}\left(\tilde{R}_{mt}, \tilde{R}_{it} | \tilde{R}_{mt} < -\delta, \tilde{R}_{it} < -\delta\right). \tag{3}$$

$|J^{Adj}| \sim \chi^2_N$ following Hong, Tu, and Zhou (2007) [6]. Where dependence is symmetric across upper and lower tails, J^{Adj} will be near zero. Conversely, any strong asymmetries in dependence between upper and lower tails will result in a significant, non-zero J^{Adj}. A positive (negative) J^{Adj} is indicative of UTD (LTD), over and above the tail dependence implied by ordinary β.

In its own right, J^{Adj} captures both LTD and UTD between a stock and the market. In order to isolate upside and downside risk for the purposes of our regression analysis, we compute:

$$J^{Adj}+ = J^{Adj}\mathbb{I}_{J^{Adj}>0} \tag{4}$$

$$J^{Adj}- = J^{Adj}\mathbb{I}_{J^{Adj}<0}, \tag{5}$$

where $\mathbb{I}_a$ is an indicator function taking a value of 1 when the condition, a, is satisfied and zero otherwise.

As a non-parametric measure of AD, the J^{Adj} statistic facilitates the separation of the actual price of tail dependence from the effect of non-normal marginal return characteristics. Furthermore, it is consistent with Stapleton and Subrahmanyam (1983) and Kwon (1985) who suggest a means of deriving a linear relationship between β and expected return without the need for multivariate normal assumptions. J^{Adj} is also consistent with the empirical evidence that correlations tend to be larger in the lower tail of the joint

[6] The transformations described represent (nonsingular) affine transformations that may ultimately be expressed as linear transformations (Webster, 1995). Birkhoff and Lane (1997) show that a nonsingular linear transformation of the space, V, is an isomorphism of the vector space, V, to itself. The assumptions used by Hong, Tu, and Zhou (2007) to derive an asymptotic distribution for the J statistic therefore holds for the transformed returns $\left\{\tilde{R}_{1t}, \tilde{R}_{2t}\right\}$. $|J^{Adj}| \sim \chi^2_N$ then follows the proof described in Hong, Tu, and Zhou (2007).

return distribution compared to the upper tail (Ang and Chen, 2002; Longin and Solnik, 2001). LTD exists provided dependence in the lower tail exceeds dependence in the upper tail. Normality in the opposite tail is not required by this definition which precludes parametric alternatives, such as the H statistic (Ang and Chen, 2002), for the purposes of our investigation.

An advantage of transforming the data in the way described above is that the standard deviation of market model residuals is forced to be the same across data sets. Controlling for the effects of idiosyncratic risk is important given the recent debate over whether idiosyncratic risk is relevant in an asset pricing context (Bali, Cakici, Yan, and Zhang, 2005; Goyal and Santa-Clara, 2003). It is often argued that idiosyncratic risk should be priced whenever investors fail to hold sufficiently diversified portfolios (Campbell, Lettau, Malkiel, and Xu, 2001; Fu, 2009; Merton, 1987). However, when tail risk is characterized by dependence that increases during down markets, the ability to diversify will be effected and the ability to protect the portfolio from risk will be reduced. Hence, downside risk may be mistakenly identified as idiosyncratic risk. Where this occurs, we expect idiosyncratic risk to increases as downside risk increases. Standardizing market model residuals allows us to distinguish between downside risk and other firm specific risks.

Note that because tail risk is estimated by analyzing the difference in correlation beyond N exceedances, the occurrence of net AD may be contingent upon a relatively small number of positive or negative joint returns. As a result, any measure of AD will suffer from a high likelihood of Type II errors making it difficult to detect AD unless large data sets are utilized. Consequently, we present conservative estimates of AD between equity returns and the market.

2 A Closer Look at the Asymmetric Dependence Risk Premium

2.1 Empirical Design

Our methodology broadly follows Ang, Chen, and Xing (2006), to build on the existing evidence of a downside risk premium in the cross-section. We analyze the contemporaneous relationship between systematic risk, AD and returns, controlling for a range of factors including size, book-to-market ratio, past 12-month excess return, idiosyncratic risk, coskewness and cokurtosis [7]. A particular factor is a relevant risk attribute if high adverse factor changes coincide with higher return, consistent with the concept of a contemporaneous risk-return relationship (Black, Jensen, and Scholes, 1972; Gibbons, 1982).

The Adjusted J measure of AD is calculated with exceedances $\delta = \{0, 0.2, 0.4, 0.6, 0.8, 1\}$ in conjunction with the Bartlett kernel, following Hong, Tu, and Zhou (2007), for the estimation of the variance-covariance matrix, $\hat{\Omega}$. We measure risk premia using the Fama and MacBeth (1973) asset pricing procedure where cross-sectional regressions are computed every month rolling forward using a 12 month window to estimate the relevant factors. We measure statistical significance using Newey and West (1987) adjusted t-statistics to control for overlapping data using the Newey and West (1994) automatic lag selection method to determine the lag length [8]. The use of short, rolling window risk factor estimates may be better positioned to account for the evidence of time variation in systematic risk (Blume, 1975; Bollerslev, Engle, and Wooldridge, 1988; Bos and Newbold, 1984; Fabozzi and Francis, 1978; Ferson and Harvey, 1991, 1993; Ferson and Korajczyk, 1995) and any potential time variation in tail dependence relative to a static model. Furthermore, estimates based on short windows are thought to have higher power in an environment where risk factors may be time varying. We test the robustness of our results to alternative window lengths

[7] A contemporaneous methodology attempts to avoid the errors-in-variables problem (Kim, 1995) that occurs when relating risk factors estimated using past data with returns in a future period using the two-pass methodology. This facilities the performance of cross sectional regression for individual securities rather than for portfolio groupings.

[8] Although the theoretical number of lags required to account for the use of overlapping data is 11, the Newey and West (1994) automatic lag selection method produces an optimal lag length of 14 given the length of data we consider.

in Section 3.1.

2.2 Data

At a given month, t, the average of the next 12 excess monthly returns is regressed against combinations of CAPM β, upside and downside β, idiosyncratic risk , coskewness, cokurtosis and J^{Adj} estimated using the next 12 months of daily excess return data, and size, book-to-market ratio, and average past 12-monthly excess return [9], computed as at time t. We measure idiosyncratic risk as the standard deviation of market model residuals. We substitute this measure for realized return volatility used by Ang, Chen, and Xing (2006) because we explicitly involve ordinary β in our regression methodology. Including β and realized return volatility, measured as the standard deviation of realized excess returns, would induce multicollinearity into our analysis and therefore bias our results. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month Treasury bill rate. All regressors are Winsorized at the 1% and 99% level at each month to control for outliers and inefficient factor estimates.

We use daily data to estimate risk factors primarily to ensure we have sufficient observations to accurately measure upside and downside risk, estimated using J^{Adj}. Although risk factor estimates computed using daily data over short periods are likely to be noisy compared to estimates computed with lower frequency data over longer periods, subsequent tests of the significance of factor risk premium will have reasonable power because they are estimated using a long time series of estimates (Lewellen and Nagel, 2006).

In order to minimize the possibility of non-synchronous trading associated with the use of daily data, we restrict our attention to stocks listed on the NYSE [10] between July

[9] We control for Pastor and Stambaugh (2003) liquidity β in a separate regression in Section 3.1 given the different data treatment required to estimate liquidity β.

[10] All data are collected from CRSP. See Appendix A for a details of our data collection process.

1963 and December 2009. The sample size at each month is depicted in Figure 5.

[Figure 5 about here]

2.2.1 Factor Correlation

Table 1 highlights the difficulty in measuring a separate premia for AD and ordinary market risk using conditional β. Computing the correlation between risk factors for our entire sample, we find that upside and downside β are both highly correlated with ordinary β, implying that conditional β cannot be included in the same regression as ordinary β due to multicollinearity.

[Table 1 about here]

Consistent with it's construction, J^{Adj} and β are virtually independent with correlation equal to 0.054, indicating that AD, be it LTD or UTD, exists independent of systematic risk. This has implications for risk management and portfolio construction. For example, two portfolios with equal βs will likely display varying degrees of market risk given the existence of AD. Significant tail dependence may have therefore contributed to the losses experienced by equity market neutral hedge funds during August of 2007 (Khandani and Lo, 2007). We investigate whether this hypothesis is evident in our sample in Section 2.6.

The orthogonality between β and J^{Adj} may also affect particular aspects of asset pricing. In particular, a zero-β portfolio may not necessarily be a risk free portfolio due to the existence of AD. Black, Jensen, and Scholes (1972) find that portfolios with zero covariance with the market display average returns that significantly exceed the risk free rate. This is consistent with the existence of tail risk that could cause the market risk of the zero-β portfolio to be significantly different from zero.

We find that J^{Adj} displays the largest correlation with return out of all variables we consider (coefficient of -0.136). Consistent with prior literature, the negative coefficient implies that stocks that display higher downside risk experience the highest average monthly return over the same period. In contrast, β and return are positively correlated as are β^- and return, however, the correlation with β^- is larger in magnitude, consistent with a market aversion to downside risk.

2.3 Distribution of J^{Adj}

We depict the distribution of AD, as measured by J^{Adj}, for all firms in our sample between 1963 and 2009 following the methodology described in the previous section. A histogram of all J^{Adj} observations reveals that the distribution of J^{Adj} is (asymmetrically) bi-modal with 67.33% of J^{Adj} observations less than zero, and the remaining 32.67% of observations greater than zero.

[Figure 6 about here]

For comparison, we include the distribution of the J^{Adj} computed using simulated multivariate normal data, parameterized at each month (Figure 6(b)). The size of each sample is chosen to match the number of days in each 12 month period. The distribution is (symmetrically) bi-modal with a statistically insignificant average of -0.004. Comparison with Figure 6(a) suggests that AD is more of a characteristic of actual returns data than what is suggested under multivariate normality.

There are likely to be a number of reasons for the observation that LTD occurs more often than UTD. One possibility is offered by Bekaert and Wu (2000) who effectively suggest that AD may be driven by the asymmetric effects of news on the conditional covariance between stock and market returns. They argue that asymmetric volatility at the firm level is a direct result of asymmetric covariance with the market. The negative price reaction caused by volatility feedback offsets the initial price increase associated with good news and amplifies the negative price reaction associated with bad news. In order to explain asymmetric volatility for individual stock returns, an asymmetric response in the covariance between stock returns and the market is required because changes in firm-specific volatility can be theoretically diversified away. Our results are consistent with Bekaert and Wu's finding that the dependence is effected more by jointly negative shocks to firm level and market level returns compared to jointly positive shocks.

2.4 Conditional Dependence Patterns

In light of the correlation among factors and between factors and returns observed in Section 2.2.1, it is important to ensure that the relationship between J^{Adj} and return does not simply reflect a relationship between return and some unidentified latent risk. We therefore investigate the interplay between dependence and return by analyzing patterns in the contemporaneous relationship between realized average return and realized risk.

We begin by informally examining the likelihood that the downside β–return relationship indirectly reflects the relationship between β and return using the double sorting methodology used by Fama and French (1992). Specifically, we first sort stocks into β deciles and then into β^- deciles within each β decile at each month between January 1963 and December 2009, and then record the equal weighted average return for each portfolio.

[Table 2 about here]

After controlling for β, we observe a positive relationship between β^- and return, but only for the highest β deciles (Table 2, Panel A). This indicates that β^- does contain some useful information regarding return variation over and above the information contained within β. However, the lack of a β^-–return relationship for the lowest deciles of β indicates that the relationship might be conditional upon particular values of ordinary β. This is consistent with our argument that it may be difficult to differentiate compensation for ordinary market risk from compensation for the risk associated with AD. Furthermore, a larger spread in the highest and lowest β deciles compared to the highest and lowest β^- deciles suggests that the strength of the relationship between β and return is stronger than the relationship between β^- and return. This could indicate a loss of information resulting from a focus on the lower tail of the joint distribution without reference to the upper tail in the calculation of β^-. As a result, information about the upper tail of the distribution might be required in the measurement of LTD and its impact on returns, providing justification for our measure of AD.

After controlling for β, we find a positive relationship between LTD and return regardless of the level of β (Panel B). The average return and the spread between the 1^{st} and 10^{th} J^{Adj} decile are also seen to increase with β. This suggests that higher returns associated with high LTD exists irrespective of β, however, compensation for differences in AD between groups become larger as β risk increases. This could imply that an increase in systematic risk coincides with an increase in downside risk when systematic risk is high, and less so when systematic risk is low. Furthermore, if a larger return spread is assumed to provide an indication of the strength of the relationship between risk and return, J^{Adj} is more capable than β^- to capture the AD risk not captured by β.

We informally test whether the observed relationship between J^{Adj} and return indirectly reflects the relationship between return and size or coskewness risk in Panel C and D respectively. We continue to find a monotonic relationship between J^{Adj} and return despite controlling for these factors. Furthermore, the return spread and average across J^{Adj} deciles for each characteristic decile is comparable in magnitude to the return spread associated with size and coskewness. This provides further evidence that the relationship between J^{Adj} and return in is not a reflection of compensation for variation in coskewness or size. The existence of an AD premium measured using J^{Adj} is therefore distinct from the risk-premia attached to these factors.

2.5 Regression Results

We apply the Fama and MacBeth (1973) methodology between 1963 and 2009, but have included regression results for the sub-sample between 1963 and 2001 in Appendix **??** to facilitate direct comparison of our results with those presented by Ang, Chen, and Xing

(2006).

Regression I and II in Table 3 Panel A indicate that our methodology is able to generate comparable results to those presented by Ang, Chen, and Xing (2006). For example, we find that β, β^- and β^+ are significantly related to returns. The sensitivity attached to conditional β implies an increase in returns of 8% pa for a 1 unit increase in β^- and a decrease in returns of 2.8% pa for a 1 unit increase in β^+ suggesting that upside and downside risk, measured by conditional β, are priced asymmetrically. A 1 unit increase in ordinary β is associated with a 13.3% pa increase in returns. The magnitude of this market risk premium estimate differs from traditional market risk premium estimates (Dimson, Marsh, and Staunton, 2003; Pastor and Stambaugh, 2001; Siegel, 1992) due to the use of equally weighted regressions. We subsequently test our results for robustness using value weighted regressions in Section 3.1. Our coefficient for β in Table 3 is similar to the coefficient reported by Ang, Chen, and Xing (2006) when computed on an average factor loading basis.

[Table 3 about here]

To assess the relative importance of systematic risk and AD risk in the cross section, we regress returns on β and J^{Adj} in regression III, controlling for the standard set of factor risks. We find that both systematic risk and AD are significantly priced. Consistent with expectations, the negative coefficient attached to the J^{Adj} factor loading implies that stocks with LTD ($J^{Adj} < 0$) attract a premium and stocks with UTD ($J^{Adj} > 0$) attract a discount. Based purely on factor loadings, a 1 unit increase in β equates to an 12.8% pa increase in returns, similar to the coefficient attached to β in regression I, whilst a 1 unit increase (decrease) in J^{Adj} equates to a 0.6% pa decrease (increase) in return. This implies that the premium for AD is only 4.69% of the premium for systematic risk. However, this interpretation ignores differences in scale between β and J^{Adj}. A 1 unit increase in β is equivalent to a 1.93 standard deviation move based on observed β standard deviation of

0.517, whereas a 1 unit increase in J^{Adj} is equivalent to only 0.162 of a standard deviation, based on observed J^{Adj} standard deviation of 6.180.

Incorporating differences in scale between β and J^{Adj} increases the importance of AD, in its own-right, relative to systematic risk in the cross-section. For example, the magnitude of the J^{Adj} risk premium, computed for a one standard deviation increase in J^{Adj}, is 56.03% of the magnitude of the β risk premium computed for a one standard deviation increase in β. This highlights the importance of accounting for the effect of changes in both systematic risk and AD on returns.

We regress returns on $J^{Adj}+$ and $J^{Adj}-$, defined in (4) and (5) respectively, in order to isolate the premia attached to upside and downside risk. After accounting for scale, we find that UTD is more important, relative to β, than LTD in the cross-section. For example, regression IV indicates that LTD, given by $J^{Adj}-$, is 34.99% of the β risk premium, whereas UTD, given by $J^{Adj}+$, is 41.58% of the β risk premium, both accounting for scale.

Replacing β with β^+ and β^- (ignoring the potential multicollinearity issue) in regression V yields little change in our results. The significance attached to β^- and β^+ indicates that censored measures of linear dependence are priced in the cross section, where in particular, downside measures are more heavily priced than upside measures. The significance attached to $J^{Adj}-$ and $J^{Adj}+$ continues to indicate that UTD and LTD attract a price in the cross section.

A significant positive (negative) relationship between lower (upper) tail dependence and return is consistent with existing evidence of a preference towards stocks that display upside risk. Given the way we measure AD, our results imply that investors may display relative disappointment aversion consistent with Skiadas' (1997) preference framework. That is, investors display conditional preference relations for all possible joint outcomes of security and market returns.

Our results suggest that higher order dependence (in the form of UTD and LTD) is as important as linear dependence in explaining the variation in returns, implying that the CAPM ignores a significant characteristic of the joint return distribution. Investors should not only be concerned with the overall level of linear dependence between stock returns and the market, they should also be concerned with the symmetry of the joint return distribution around β.

MacKinlay (1995) argues that if a set of factors results in a zero mispricing vector, then a linear combination of these factors can be combined to define the market portfolio, consistent with Sharpe (1977). Inefficiencies in the market proxy will therefore affect the linear relationship between β and return and may cause other variables to have explanatory power in cross-sectional asset pricing tests (Roll and Ross, 1994). A proxy for the market portfolio may be mean-variance inefficient if the number of assets in the proxy do not lead to complete convergence to multivariate normality. The significance of firm specific factors in cross-sectional tests might therefore reflect the slow convergence of higher order dependence terms to zero for the most commonly used market proxies. We consider with the speed of convergence to normality drives our results in Section 3.

If expected returns can be written as a linear function of k factors, then k-fund separation can be used to span the mean-variance efficient frontier (Fama, 1996; Ross, 1978). This implies that a mean-variance efficient portfolio defined by linear dependence is unlikely to be efficient with respect to an efficient portfolio spanned by both linear and asymmetric dependence. This suggests that the risk of a well diversified portfolio will reflect both the average covariance and the average tail dependence between the assets.

Using deep out-of-the-money index options, Bollerslev and Todorov (2009) show that compensation for investor fear towards low probability, highly catastrophic events accounts for a substantial fraction of the equity risk premium in the US market. When applied to individual equities, the risk premium for downside risk is likely to depend on the magnitude of the relationship between the stock's returns and the aggregate market. Our results suggest that there need only be a tendency for stocks to display higher dependence during market downturns relative to upturns for a tail dependence risk premia to arise. This is a weaker condition than the requirement of a low probability, highly catastrophic market crash. Of course, what would otherwise be a market decline can quickly precipitate into a potential market crash in the presence of levered positions in tail risk. In particular, Diamond and Rajan (2009) and Rajan (2006) describe an incentive for managers to load up on 'hidden' downside risk in the form of tail risk and report the compensation as reward for α. This may partly explain the excess risk taken by managers prior to the 2007-2009 financial crisis.

2.6 Time Varying Risk

Tail-risk management has been of increasing concern amongst practitioners in recent years, particularly in the aftermath of the sub-prime crisis and the ensuing global financial crisis (Bhansali, 2008). The development of a superior tail-risk management product therefore represents a potentially important and lucrative enterprize as the economy recovers and proceeds into the next boom-bust cycle. In the absence of a zero-cost tail risk hedge, investors must identify whether such products are justified in light of what drives market crashes historically, and the likelihood of these drivers being associated with future market failures. Products that manage changes in linear dependence are likely to look much different from products that manage changes in AD. However, products that target increases in systematic risk when crashes are driven by changes in AD (and vice versa) may not adequately protect portfolios during market crashes. In order to identify the extent that investors should be concerned with this problem, we examine the relative importance of systematic risk (changes in linear dependence) and AD (changes in higher order dependence) over time.

The increasing concern for tail-risk management is likely to reflect either an increase in the sensitivity of individual securities to market movements, an increase in aversion to risk, or some combination of the two. To capture potential changes in aversion to risk, we re-estimate model IV of Table 3 using the Fama and MacBeth (1973) procedure at each month t between January 1989 and January 2009. The factor premium at time t is then given by the median of all regression coefficients associated with that factor up to and including time t. We have chosen to compute the factor premium using medians because we are interested in the trend in risk premium over time rather than an accurate portrayal of the compensation for risk. Short-term, non-permanent increases in regression coefficients are likely to result in permanent changes in risk premium estimates computed using averages over all historical coefficient estimates. Changes in the median regression coefficient are therefore more likely to reflect permanent trend changes rather than short-term trend changes. Similarly, we capture changes in the factor loadings by computing the median of a given factor at time t using all observations up to and including t.

An inspection of the average loading attached to β, $J^{Adj}-$ and $J^{Adj}+$ indicates that the heightened concern for tail risk management is unlikely to be a result of changes in stock sensitivity to market movements (Figure 7(a)). To highlight this point, observe that the median loading on $J^{Adj}-$ between 2007 and 2009 appears no greater than the median loading immediately prior to this [11] , indicating that the sensitivity to market crashes has not altered significantly, relative to historical sensitivity, in response to the financial crisis. Similarly, there was an increase in systematic risk (β) between 2007 and 2009, however the magnitude of this increases does not differ significantly from the level of increase that began in 2001.

A plot of the factor sensitivity attached to β (per unit of factor loading) highlights the change in the price of systematic risk corresponding to the run up in prices during the 1990s (Figure 7(b)). Despite the use of medians in our estimation of risk premia, the magnitude of this sensitivity subsequently remains at this heightened level with only a slight decrease from November 2006 onwards. This implies that systematic risk is priced

[11] This observation holds after scaling by the standard deviation of $J^{Adj}-$ at each month.

at a higher level between 2000 and 2009 compared to the previous decade. Furthermore, the run-up in prices during the 1990s had more of an effect on the reward for systematic risk than the market turmoil of 2007-2009. Combined with the slight increase in β loading over this time, the net effect is a slight increase in the β risk premium during the financial crisis.

[Figure 7 about here]

Interestingly, the positive premium attached to LTD has remained relatively constant between 1989 and 2009, suggesting that LTD has been priced in equities for a long period of time. The discount attached to upside potential, on the other hand, increased markedly between 1990 and 2007 and decreased slightly from 2007 onwards. Taken together, this implies that the market became more downside risk averse overall, but more as a result of increased demand for stocks displaying sensitivity to market upturns rather than as a result for an increased aversion to stocks with downturn sensitivity. In the context of Skiadas' downside risk framework, where disappointment is judged with respect to outcomes that could have occurred, this implies that a stock with constant downside market sensitivity will attract an increasing risk premia over time due to the increasing importance of stocks that generate elating outcomes.

On the basis of changes in risk premia, the 2007-2009 financial crises appears to be as much a systematic risk story as it is a tail risk story implying that the risks associated with both linear dependence and higher-order dependence should be managed to insulate a portfolio from future market crashes. For many investors, techniques to manage changes in systematic risk are likely to be already in place, particularly through the ability to tactically allocate funds between assets on the basis of changes in overall fundamentals. A value accreting tail-risk management product should therefore target changes in tail dependence over and above the tail dependence implied by β. Furthermore, such products should account for changes in the relative aversion to upside and downside market movements.

3 Robustness

3.1 Alternative Data Specifications

We analyze the magnitude of the AD risk premium, relative to the premium for β, for alternative data frequencies and window lengths. We perform this test for two reasons. First, given that risk and return are measured using 12 month rolling windows in Section 2.6, there is a possibility that our risk measures are not actually contemporaneously related to returns. An example might be if stocks tended to increase early within the window, thereby increasing the chance of stocks having a very negative return later in the window (reverse causality). Although we expect the use of overlapping data to largely preclude this, we seek to rule out this possibility by re-performing our regressions using alternative window sizes for estimation purposes. Second, it is possible for our measure of AD to reflect market microstructural characteristics given the use of daily data. For example, non-synchronous trading has been known to bias inferences of the temporal behavior of asset returns (Lo and MacKinlay, 1990; Shanken, 1987). To ensure the robustness of our results to this problem, we analyze the magnitude of the premium for AD, relative to the premium for β, using alternative data frequencies.

We present Fama and MacBeth (1973) regression results based on risk factor estimates computed using 6, 24 and 60 months worth of daily data, 3 and 5 years worth of weekly data and 5 years worth of fortnightly data, where estimation takes place each month rolling forward. We find that UTD, LTD, β and downside β are significant using any of the daily data specifications we consider (Table 4). The effect of moving from a 60 month window to a 6 month window appears to be an increase in the importance of the AD risk premium relative to the premium attached to β risk (the premium attached to J^{Adj} is 6.2% and 82.9% of the β premium per standard deviation of loading for the 60 month and

6 month window respectively). For our results in Section 2.6 to reflect reverse causality within our chosen window size, we would expect the sensitivity attached to J^{Adj} to become smaller in magnitude and less significant. This indicates that our results reflect an actual contemporaneous relationship between risk and return and not reverse causality within our chosen window size.

[Table 4 about here]

We do not find that market microstructural biases are sufficient to explain our main results on the basis that shifting to weekly or fortnightly data does not eliminate the significance attached to $J^{Adj}-$. For example, the coefficient attached to $J^{Adj}-$ is insignificant for fortnightly and weekly data with a 5 year window, but is significant for weekly data with a three year window. For microstructural bias in daily data to drive our results, we should not expect significance for any window length using lower frequency data.

Inspection of the similarities in the mean and standard deviation of J^{Adj} estimates across scenarios in Panel B suggests that the insignificance of J^{Adj} for long data lengths reflects a breakdown in the relationship between AD risk and return rather than convergence to normality following the central limit theorem (Cont, 2001; Kullmann, Kertesz, Toyli, Kaski, and Kanto, 2000). AD exists, but is not priced over longer horizons [12] whereas systematic risk is priced regardless of the window length. This suggests the market is risk averse in general, but displays disappointment aversion over short intervals.

This is reminiscent of the investor preferences considered by Benartzi and Thaler (1995) in their explanation of the equity premium puzzle. Specifically, loss averse investors are found to be indifferent between stocks and bonds provided their evaluation period is in the neighborhood of one year [13] . Benartzi and Thaler (1995) suggest that short evaluation

[12] Although $J^{Adj}-$ is statistically significant using daily data with a 60 month window, the magnitude of the sensitivity is economically insignificant in comparison to the $J^{Adj}-$ sensitivity computed using smaller window lengths.

[13] Benartzi and Thaler (1995) differentiate between investment horizon, which can be greater than 1 year, and an evaluation period referring to the length of time before the investor evaluates the performance of their portfolio with respect to their objectives.

horizons arise as a result of agency costs in the case of pension and endowment fund managers, and as a result of receiving comprehensive information about investments and having to file taxes annually in the case of individuals. Fielding and Stracca (2007) find that short evaluation horizons are necessary to explain the historical equity risk premium using loss aversion, whereas longer evaluation horizons can be accommodated if it is assumed that investors are disappointment averse in framework developed by Gul (1991). A combination of myopic loss aversion and disappointment aversion could therefore result in the observations of Table 4.

Value weighted regressions fail to eliminate the significance associated with β, $J^{Adj}-$ or $J^{Adj}+$ and actually increase the importance of AD relative to systematic risk accounting for differences in scale between β and J^{Adj}.

The second last column of Table 4 presents regression results using non-overlapping data. Risk factors are estimated using daily returns each fiscal year and are regressed on average monthly returns over the same period. Non-overlapping data reduces the sample size and subsequently has lower power in determining an AD risk premium. Nevertheless, we find β and $J^{Adj}-$ to be significant (we use ordinary t-statistics to determine the significance) factors in explaining return variation. Inspection of the standard deviation attached to β suggests that β is estimated inefficiently compared to the overlapping data case. In contrast, the standard deviation attached to $J^{Adj}-$ differs little when moving from overlapping to non-overlapping data. The net result is an AD risk premium that represents only 10.16% of the premium attached to β, accounting for scale. Although this differs substantially compared to the results of Section 2.6, a different conclusion may be drawn if non-overlapping regressions were performed with factor estimates computed over a much longer period of time than 12 months.

Finally, our results are unchanged when controlling for aggregate liquidity risk, measured by the Pastor and Stambaugh (2003) liquidity β, in the final column of Table 4.

3.2 Predictive Results

Consistent with prior asset pricing research, we have shown that LTD (UTD) is contemporaneously related with higher (lower) return. To further test the extent that AD is priced, relative to systematic risk, and to ensure the robustness of our contemporaneous methodology, we determine whether past estimates of AD affect future return.

We analyze the relationship between past dependence, estimated using the previous 12 months of daily excess returns data, and the average next month excess return using the Fama and MacBeth (1973) procedure. We do not find significant coefficients attached to β^- or β^+, however, we do observe significant coefficients associated with β and $J^{Adj}+$ (Table 5). The premium attached to $J^{Adj}+$ is 24.44% of the premium attached to β, which provides additional support in favor of the contemporaneous relationship between the AD premium relative to the market risk premium explored in Section 2.6. The coefficient attached to β is negative (-5.6% pa), however, indicating the existence of a negative ex ante risk premium, consistent with Boudoukh, Richardson, and Smith (1993) and Eleswarapu and Thompson (2007).

[Table 5 about here]

Ang, Chen, and Xing (2006) investigate the role played by volatility in measuring the relationship between past upside and downside β and future return. They argue on the one hand that high return volatility could lead to less accurate β^- estimates thereby reducing the ability to predict future β^-. Alternatively, they suggest a confounding relationship between β^- and stock volatility which is compounded by the possibility that stocks with very high volatility have extremely low returns, as demonstrated by Ang, Hodrick, Xing, and Zhang (2006). The remedy for this problem is to consider the relationship between past dependence and future return, excluding the most volatile stocks.

We investigate the role of volatility on our predictive results following Ang, Chen, and Xing (2006) by measuring volatility as the standard deviation of excess daily returns estimated over the past 12 months. Excluding the top quintile of volatile stocks each month causes the coefficient attached to β to become insignificant, suggesting that volatility plays an important role in the β predicability of future return. Furthermore, the coefficient attached to $J^{Adj}+$ is now insignificant, but is replaced by a significant $J^{Adj}-$ sensitivity. Excluding the top decile and the top 5%-tile of volatile stocks only serves to increases the value of the $J^{Adj}-$ sensitivity and its associated t-statistic. Hence, AD is more important than linear dependence in forecasting the returns of the least volatile stocks. Across the entire sample, the importance of tail dependence continues to represent only a fraction of the importance associated with linear dependence in explaining equity return variation.

4 Conclusion

The aim of this paper is quantify the size of the AD premium relative to the market risk premium. This investigation is motivated by the need to identify whether the effect of an apparent tail event on returns reflects compensation for changes in tail dependence (symmetry) or compensation for changes in systematic risk (linear dependence). To measure AD, we employ a linear (β) dependence invariant metric, based on the J statistic originally proposed by Hong, Tu, and Zhou (2007).

We find that the magnitude the premium associated with AD is a substantial fraction of the premium associated with β, highlighting the importance of accounting for the effect of changes in both systematic risk and tail dependence on returns. We also find that UTD is more important, relative to β, than LTD in the cross-section. Both the prevalence and price of UTD has been increasing in recent years, indicting that investors are valuing UTD more, while more firms are exhibiting this value-adding characteristic. Over time, the premium attached to LTD remains relatively constant and has been priced in the cross-section for a long period. As a result, the market environment in large cap equities between 2007 and 2009 can be explained in part by changes in systematic risk, but also by changes in the importance of stocks that display UTD with the market.

These results have important practical implications, particularly for future endeavours to manage tail risk. Buyers and sellers of tail risk protection both need to carefully consider the likely magnitude of systematic risk changes relative to changes in AD. A strategy that hedges the risk associated with changes in linear dependence may be significantly different from the strategy an investor might otherwise put in place to manage changes in tail dependence. By analyzing the magnitude of the sensitivity of returns to AD, relative to the sensitivity of returns to systematic risk, investors may be able to assess whether systematic risk hedges are sufficient to mitigate the potential losses associated with tail dependence.

Our results also have significant implications for a firms cost of capital and the associated capital raising decisions. The existence of AD between the firms returns and those of the market will induce a corresponding discount (UTD) or premium (LTD). Failing to recognise the influence of AD on the cost of capital is likely to render public capital offerings either underpriced or undersubscribed. Similarly, capital managers who recognise the value of AD are likely to be able to generate measurable alpha by exploiting the associated premium. However this alpha is not without risk. In order to identify whether this alpha is 'genuine', suitable AD sensitive performance measures need to be identified and utilised. Our results also suggest that such measures are unlikely to be based upon Copula parameters, β or downside β.

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A Data Collection Methodology

Our data collection methodology attempts to follow Ang, Chen, and Xing (2006) in order to generate comparable results. We use data from the CRSP database, collected through Wharton Research Data Services (WRDS). Using the daily stock file, we collect share code, permno, price, holding period return, and number of shares outstanding between 01 July 1962 and 31 December 2009. For our main analysis, we only include data for stocks with exchange code (exchcd) equal to 1 (NYSE data).

We use all unique permnos to obtain book value data using the CRSP/COMPUSTAT Merged database. We collect "Common/Ordinary Equity - Total" (CEQ) data, restricting our attention to link types "LC" and "LU". Stocks with multiple company names for a given permno are excluded. The risk free rate is proxied by the 1 month T-bill rate, collected from the Kenneth R. French Data Library [14]. The market portfolio is proxied by the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks.

We calculate the relevant variables for a given month, t, for those stocks with data for months $t-12$ to $t+12$, and for those stocks that have a sharecode of 10 or 11 for that

[14] We thank Ken French for making this data available.

period. Holding period returns, r_h are converted to continuously compounded returns, r_c by setting $r_c = \log(1 + r_h)$.

Market capitalizations are computed as the absolute value of the product of share price and total shares outstanding[15] . We use book-values from the previous year whenever the month at time t is less than 6, and current year book-values whenever the month at time t is great than or equal to 6. Book-to-market ratio is then computed using current market cap at time t. Any stock with missing book value data is assigned a BM ratio of zero.

In order to compute excess daily returns, we take the risk free rate at a given month and divide by the number of days for that month. Regular β, upside and downside β, realized volatility, coskewness and cokurtosis are then computed according to equation (B-7) to (B-9) of Ang, Chen, and Xing (2006).

Finally, we compute Pastor and Stambaugh (2003) liquidity β for our NYSE stock data following the methodology described by Ang, Chen, and Xing (2006, pg. 1236). We obtain data on the innovation in aggregate liquidity from WRDS.

[15] CRSP assigns a negative sign to price in the event that closing price is not available for a given trading day. The bid/ask average is instead reported on that day.

Tables and Figures

Factor Correlation

Table 1. This table presents the correlation between each factor. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009. At each month, t, we estimate β, β^-, β^+, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj} estimated using the next 12 months of daily excess return data, and size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret") computed as at time t. Returns ("Ret") are estimated as the average of the next 12 monthly excess return. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All factors are Winsorized at the 1% and 99% level at each month.

	β	β^-	β^+	Log-size	BM	Past Ret	Idio	Cosk	Cokurt	J^{Adj}	Ret
β	1	0.804	0.786	0.101	-0.070	0.177	0.226	-0.017	0.170	0.054	0.068
β^-		1	0.515	-0.011	-0.039	0.167	0.229	-0.137	0.144	-0.083	0.099
β^+			1	0.135	-0.063	0.126	0.125	0.111	0.168	0.204	0.016
Log-size				1	-0.312	0.089	-0.296	-0.079	0.142	0.088	-0.077
BM					1	-0.071	0.170	0.059	-0.076	-0.001	0.107
Past Ret						1	-0.081	-0.070	0.050	-0.016	-0.023
Idio							1	0.015	-0.034	-0.003	-0.093
Cosk								1	-0.827	0.260	0.004
Cokurt									1	0.019	-0.033
J^{Adj}										1	-0.136
Ret											1

The Time Series Average Returns for Double Sorted Portfolios

Table 2. For a given month, we first sort stocks into β deciles, and then into β^- or J^{Adj} deciles within each characteristic decile in Panel A and B respectively. In Panel C and D, we first sort stocks into size or coskewness deciles respectively, and then into J^{Adj} deciles within each characteristic decile. Dependence ranges from low (group 1) to high (group 10) which implies that J_1^{Adj} consists of the stocks with high downside risk and J_{10}^{Adj} consists of stocks with high upside potential. We record and report the equal weighted average 12 monthly excess return for all stocks within each group, expressed as an effective annual rate of return. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. We provide the spread ("Diff") for each row and column, given by the return associated with the high risk group, less the return associated with the low risk group. We also include the average return ("Avg") for each row and column.

Panel A: β/β^- Sorted Portfolios

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	Diff	Avg
β_1^-	0.027	0.010	0.029	0.025	0.010	0.022	0.025	0.030	0.031	0.050	0.023	0.026
β_2^-	0.034	0.050	0.043	0.050	0.065	0.065	0.062	0.076	0.065	0.079	0.045	0.059
β_3^-	0.040	0.051	0.044	0.064	0.066	0.063	0.070	0.095	0.083	0.110	0.070	0.069
β_4^-	0.039	0.052	0.064	0.074	0.071	0.077	0.087	0.094	0.110	0.134	0.094	0.080
β_5^-	0.038	0.054	0.062	0.075	0.079	0.076	0.096	0.108	0.104	0.151	0.114	0.084
β_6^-	0.042	0.053	0.065	0.078	0.085	0.090	0.099	0.121	0.119	0.176	0.133	0.093
β_7^-	0.048	0.052	0.067	0.078	0.084	0.096	0.101	0.122	0.123	0.171	0.123	0.094
β_8^-	0.041	0.049	0.070	0.081	0.094	0.102	0.113	0.121	0.137	0.232	0.191	0.104
β_9^-	0.048	0.058	0.078	0.089	0.099	0.112	0.126	0.113	0.156	0.240	0.191	0.112
β_{10}^-	0.029	0.085	0.085	0.092	0.108	0.120	0.110	0.119	0.159	0.214	0.185	0.112
Diff	0.002	0.075	0.056	0.067	0.098	0.098	0.085	0.088	0.128	0.165		
Avg	0.039	0.051	0.061	0.071	0.076	0.082	0.089	0.100	0.109	0.156		

Panel B: β/J^{Adj} Sorted Portfolios

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	Diff	Avg
J_1^{Adj}	0.089	0.114	0.116	0.124	0.132	0.128	0.150	0.159	0.175	0.281	0.192	0.147
J_2^{Adj}	0.071	0.094	0.100	0.110	0.123	0.129	0.132	0.139	0.170	0.220	0.149	0.129
J_3^{Adj}	0.059	0.076	0.089	0.099	0.107	0.112	0.116	0.136	0.138	0.203	0.144	0.114
J_4^{Adj}	0.050	0.078	0.087	0.097	0.093	0.107	0.104	0.123	0.144	0.195	0.145	0.108
J_5^{Adj}	0.050	0.063	0.073	0.089	0.093	0.107	0.106	0.120	0.122	0.188	0.139	0.101
J_6^{Adj}	0.038	0.045	0.058	0.068	0.079	0.080	0.089	0.106	0.118	0.156	0.118	0.084
J_7^{Adj}	0.030	0.033	0.048	0.054	0.067	0.076	0.081	0.085	0.088	0.134	0.104	0.070
J_8^{Adj}	0.014	0.030	0.036	0.047	0.042	0.049	0.066	0.061	0.064	0.090	0.076	0.050
J_9^{Adj}	0.006	0.005	0.021	0.023	0.032	0.042	0.041	0.055	0.054	0.072	0.066	0.035
J_{10}^{Adj}	-0.017	-0.019	-0.015	0.000	-0.004	-0.002	0.008	0.017	0.018	0.025	0.041	0.001
Diff	0.105	0.134	0.130	0.124	0.135	0.130	0.142	0.142	0.157	0.256		
Avg	0.039	0.052	0.061	0.071	0.076	0.083	0.089	0.100	0.109	0.156		

The Time Series Average Returns for Double Sorted Portfolios Continued

Table 2. Continued.

Panel C: Size/J^{Adj} Sorted Portfolios

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	Diff	Avg
J_1^{Adj}	0.246	0.151	0.183	0.154	0.141	0.123	0.108	0.109	0.095	0.068	0.178	0.138
J_2^{Adj}	0.228	0.132	0.159	0.149	0.116	0.102	0.108	0.094	0.078	0.066	0.162	0.123
J_3^{Adj}	0.197	0.135	0.142	0.132	0.103	0.114	0.101	0.092	0.079	0.066	0.131	0.116
J_4^{Adj}	0.159	0.119	0.135	0.105	0.102	0.096	0.089	0.093	0.075	0.062	0.097	0.104
J_5^{Adj}	0.167	0.108	0.122	0.096	0.089	0.096	0.082	0.085	0.067	0.055	0.111	0.097
J_6^{Adj}	0.155	0.104	0.101	0.097	0.082	0.092	0.082	0.074	0.072	0.053	0.101	0.091
J_7^{Adj}	0.118	0.078	0.093	0.064	0.063	0.073	0.071	0.060	0.047	0.040	0.078	0.071
J_8^{Adj}	0.097	0.039	0.065	0.063	0.057	0.065	0.058	0.054	0.045	0.025	0.072	0.057
J_9^{Adj}	0.043	0.022	0.046	0.041	0.045	0.038	0.041	0.047	0.031	0.013	0.031	0.037
J_{10}^{Adj}	0.001	-0.019	-0.004	0.000	0.008	0.005	0.011	0.012	0.014	-0.001	0.002	0.003
Diff	0.245	0.169	0.186	0.154	0.133	0.118	0.097	0.097	0.081	0.070		
Avg	0.141	0.087	0.104	0.090	0.081	0.080	0.075	0.072	0.060	0.045		

Panel D: Coskewness/J^{Adj} Sorted Portfolios

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	Diff	Avg
J_1^{Adj}	0.183	0.192	0.169	0.161	0.159	0.139	0.113	0.091	0.088	0.073	0.110	0.137
J_2^{Adj}	0.168	0.176	0.154	0.148	0.127	0.114	0.104	0.084	0.077	0.051	0.118	0.120
J_3^{Adj}	0.165	0.167	0.141	0.131	0.109	0.105	0.092	0.077	0.051	0.044	0.121	0.108
J_4^{Adj}	0.153	0.144	0.132	0.129	0.097	0.108	0.088	0.071	0.052	0.035	0.118	0.101
J_5^{Adj}	0.149	0.140	0.131	0.110	0.092	0.091	0.089	0.058	0.035	0.011	0.138	0.091
J_6^{Adj}	0.143	0.138	0.128	0.118	0.094	0.085	0.069	0.042	0.031	0.020	0.123	0.087
J_7^{Adj}	0.123	0.130	0.113	0.094	0.073	0.061	0.053	0.037	0.027	0.012	0.111	0.072
J_8^{Adj}	0.123	0.121	0.095	0.079	0.064	0.053	0.041	0.031	0.013	-0.005	0.128	0.062
J_9^{Adj}	0.094	0.103	0.073	0.068	0.041	0.032	0.036	0.022	-0.004	-0.008	0.102	0.046
J_{10}^{Adj}	0.045	0.056	0.039	0.029	0.014	0.014	0.001	-0.006	-0.014	-0.040	0.085	0.014
Diff	0.139	0.136	0.130	0.132	0.146	0.124	0.112	0.097	0.102	0.113		
Avg	0.135	0.137	0.118	0.107	0.087	0.080	0.069	0.051	0.036	0.019		

Fama and MacBeth (1973) Regressions (1963-2009)

Table 3. We measure risk premia using the Fama and MacBeth (1973) asset pricing procedure where cross-sectional regressions are computed every month rolling forward. At a given month, t, the average of the next 12 excess monthly returns is regressed against β, β^-, β^+, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj} estimated using the next 12 months of daily excess return data, and size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret"), computed as at time t. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009. Statistical significance is determined using Newey and West (1987) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994) automatic lag selection method to determine the lag length. The mean and standard deviation (in parentheses) for each variable is provided at the last column. All coefficients are reported as effective annual rates.

	I	II	III	IV	V	mean (std)
Int	0.351	0.029	0.325	0.328	0.303	
	[4.69]	[1.70]	[4.60]	[4.56]	[4.33]	
β	0.133		0.128	0.129		0.901
	[3.81]		[3.74]	[3.73]		(0.517)
β^-		0.080			0.127	0.970
		[4.31]			[4.37]	(0.635)
β^+		-0.028			-0.043	0.846
		[2.60]			[2.51]	(0.680)
Log-size	-0.038		-0.037	-0.037	-0.033	5.946
	[5.07]		[5.04]	[5.06]	[4.85]	(1.799)
BM	0.019		0.019	0.019	0.018	0.769
	[2.52]		[2.49]	[2.48]	[2.38]	(0.663)
Past Ret	-0.015		-0.012	-0.012	-0.007	0.147
	[1.21]		[0.97]	[0.95]	[0.58]	(0.440)
Idio	-0.356		-0.349	-0.349	-0.316	0.341
	[3.68]		[3.64]	[3.65]	[3.34]	(0.185)
Cosk	-0.191		-0.071	-0.068	0.332	-0.125
	[4.90]		[2.60]	[2.51]	[3.98]	(0.426)
Cokurt	0.018		0.024	0.023	0.047	2.195
	[1.35]		[1.85]	[1.80]	[3.49]	(4.087)
J^{Adj}			-0.006			-2.127
			[5.25]			(6.180)
$J^{Adj}-$				-0.006	-0.008	-5.757
				[4.65]	[5.02]	(3.4113)
$J^{Adj}+$				-0.009	-0.009	5.362
				[3.83]	[3.96]	(3.1164)

Alternative Fama and MacBeth (1973) Regression Specifications (1963-2009)

Table 4: We measure risk premia using the Fama and MacBeth (1973) asset pricing procedure where cross-sectional regressions are computed every month rolling forward. Risk factors are estimated each month rolling forward and are calculated using 60, 24 and 6 months worth of daily data, 5 and 3 years worth of weekly data and 5 years worth of fortnightly data. We also include value-weighted regression results, non-overlapping data regression results and a regression that controls for Pastor and Stambaugh (2003) liquidity β. This final regression estimates premia between 1968 and 2009 as the first 5 years of data are used to estimate β_L. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009. With the exception of the non-overlapping data regression, statistical significance is determined using Newey and West (1987) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994) automatic lag selection method to determine the lag length. All coefficients in Panel A are reported as effective annual rates. The mean and standard deviation for each variable is provided in Panel B. Note that for the value weighted regressions, we calculate the value weighted mean and value weighted standard deviation of each risk factor at each month and report the time series average value weighted mean and the time series average value weighted standard deviation.

Panel A: Regression Results

	Daily						Weekly				Fortnightly				
	60 mth		24 mth		6 mth		5 yr		3 yr		5 yr				
	I'	IV'	I'	IV'	I'	IV'	I'	IV'	I'	IV'	I'	IV'	VW	Non-OL	Liquidity
Int	0.310	0.314	0.339	0.347	0.222	0.218	-0.084	-0.005	-0.105	-0.030	-0.010	-0.017	0.089	-0.019	0.305
	[5.94]	[6.02]	[5.03]	[5.07]	[3.37]	[3.50]	[0.93]	[0.08]	[1.16]	[0.42]	[0.20]	[0.36]	[2.62]	[0.58]	[4.71]
β		0.140		0.154		0.086		0.134		0.162		0.047	0.097	0.239	0.126
		[4.84]		[3.94]		[3.38]		[3.23]		[2.56]		[2.37]	[2.94]	[9.01]	[3.67]
β^-	0.084		0.119		0.065		-0.189		-0.113		0.037				
	[4.69]		[4.30]		[3.58]		[0.99]		[0.87]		[1.45]				
β^+	0.04		0.00		-0.03		0.16		0.11		-0.02				
	[2.39]		[0.11]		[2.29]		[1.18]		[1.03]		[0.86]				
BM	-0.03	-0.04	-0.04	-0.041	-0.02	-0.025	-0.02	-0.014	-0.01	-0.011	-0.01	-0.010	0.024	-0.012	-0.033
	[6.15]	[6.16]	[5.40]	[5.50]	[4.09]	[4.21]	[4.26]	[2.12]	[3.36]	[1.48]	[2.61]	[2.32]	[1.93]	[2.92]	[5.33]
Log-Size	0.014	0.01	0.016	0.016	0.024	0.025	0.001	0.001	0.002	0.002	0.001	0.001		0.007	0.025
	[3.49]	[3.45]	[2.61]	[2.62]	[3.03]	[3.09]	[3.25]	[2.59]	[1.80]	[2.07]	[1.41]	[1.68]		[1.99]	[2.48]
Past Ret	-0.024	-0.025	-0.027	-0.028	0.024	0.021	-0.045	-0.049	-0.044	-0.059	-0.023	-0.025	0.028	0.015	-0.017
	[4.14]	[4.40]	[2.98]	[3.02]	[1.11]	[0.99]	[2.69]	[2.81]	[2.10]	[2.09]	[3.65]	[4.10]	[2.11]	[0.86]	[1.15]
Idio	-0.162	-0.167	-0.268	-0.288	-0.202	-0.291	0.481	0.256	0.600	0.344	0.273	0.265	-0.349	0.133	-0.357
	[4.85]	[5.07]	[4.11]	[4.36]	[1.29]	[2.07]	[2.44]	[3.11]	[2.93]	[3.23]	[4.06]	[3.92]	[3.42]	[1.61]	[4.00]
Cosk	-0.058	-0.083	-0.007	-0.104	0.048	0.024	-0.508	-0.003	-0.479	-0.012	0.096	0.020	-0.071	-0.202	-0.032
	[1.88]	[3.94]	[0.13]	[3.44]	[0.84]	[1.05]	[1.09]	[0.11]	[1.01]	[0.42]	[1.46]	[1.30]	[2.39]	[9.49]	[1.22]
Cokurt	0.017	0.018	0.036	0.024	0.044	0.016	-0.036	0.003	0.000	-0.027	0.038	0.017	-0.019	-0.063	0.017
	[2.55]	[3.10]	[3.05]	[2.39]	[3.00]	[1.13]	[0.50]	[0.29]	[0.00]	[0.73]	[3.48]	[2.58]	[2.11]	[3.72]	[1.48]
$J^{Adj}-$		-0.001		-0.003		-0.010		0.000		-0.002		-0.002	-0.003	-0.007	-0.007
		[2.91]		[4.27]		[5.77]		[0.10]		[2.45]		[1.60]	[3.15]	[5.68]	[4.11]
$J^{Adj}+$		-0.002		-0.003		-0.012		-0.005		-0.002		-0.002	-0.005	0.001	-0.008
		[2.94]		[1.87]		[4.96]		[1.03]		[1.31]		[1.84]	[2.79]	[1.48]	[4.13]
β_L															0.002
															[0.36]

Alternative Fama and MacBeth (1973) Regression Specifications (1963-2009) Continued

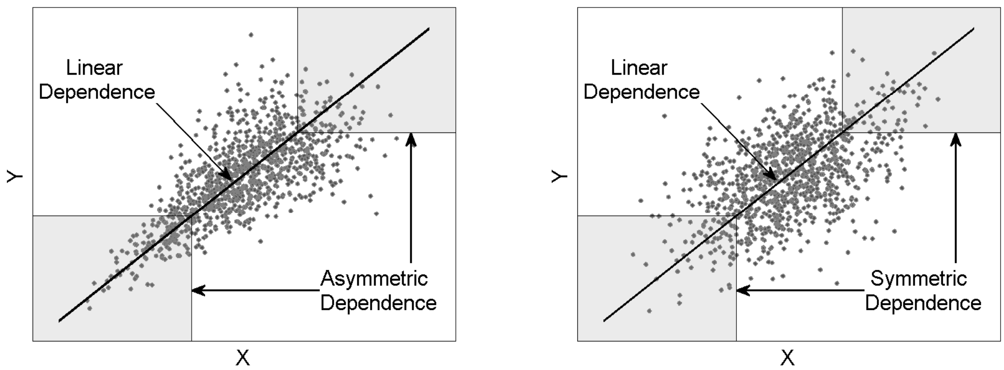
Table 4: Continued.

Panel B: Statistics																		
	Daily						Weekly				Fortnightly							
	60 mth		24 mth		6 mth		5 yr		3 yr		5 yr		VW		Non-OL		Liquidity	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
β	0.886	0.418	0.902	0.475	0.897	0.574	0.958	0.414	0.973	0.457	1.006	0.454	1.000	0.173	0.973	1.106	0.893	0.490
β^-	0.939	0.446	0.969	0.541	0.965	0.779	0.995	0.489	1.022	0.583	1.012	0.569	0.972	0.221	0.880	4.744	0.943	0.593
β^+	0.844	0.465	0.852	0.569	0.842	0.855	0.924	0.548	0.933	0.662	0.968	0.682	1.037	0.293	0.330	0.154	0.855	0.634
BM	5.937	1.751	5.952	1.789	5.936	1.803	5.960	1.722	5.990	1.739	5.951	1.719	8.494	1.854	0.256	-0.132	6.213	1.839
Log-Size	0.770	0.602	0.766	0.630	0.767	0.689	1.606	4.816	1.584	4.636	1.606	4.816	0.545	0.155	2.067	-4.170	0.850	0.631
Past Ret	0.157	0.431	0.154	0.435	0.143	0.444	0.238	0.522	0.240	0.530	0.232	0.517	0.150	0.090	0.012	-4.927	0.144	0.426
Idio	0.735	0.305	0.477	0.237	0.240	0.138	0.712	0.287	0.560	0.250	0.689	0.283	0.241	0.010	0.757	0.638	0.327	0.174
Cosk	-0.280	0.744	-0.167	0.558	-0.099	0.359	-0.152	0.321	-0.143	0.349	-0.128	0.337	-0.135	0.044	0.787	0.837	-0.127	0.467
Cokurt	6.170	13.251	3.161	7.353	1.680	2.426	2.490	1.831	2.127	1.671	2.371	1.272	3.177	3.493	1.449	0.479	2.331	4.471
$J^{Adj}-$	-5.815	3.691	-5.737	3.397	-6.380	4.034	-5.623	3.243	-6.181	3.731	-5.905	3.603	-3.115	7.813	-6.213	3.838	-5.680	3.355
$J^{Adj}+$	5.778	3.450	5.375	3.077	5.890	3.698	4.944	2.882	5.446	3.314	4.953	3.026	2.282	6.128	3.654	2.603	5.449	3.123
β_L	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.004	0.243

Predictive Regressions

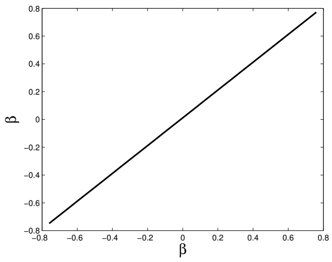
Table 5: This table presents predictive regression results of the next monthly excess return regressed upon past risk factors. At a given month, t, the average of the next excess monthly return is regressed against β, β^{-}, β^{+}, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt"), $J^{Adj}-$ and $J^{Adj}+$ estimated using the past 12 months of daily excess return data. We also include the average past 12-monthly excess return ("Past Ret"). The relevant book-to-market ratio ("BM") at time t for a given stock is computed using the last available (most recent) book value entry. Size ("Log-size") is computed at the same date that Book-to-market ratio is computed. We provide regression results using all available observations, as well as a series of regressions excluding the top quintile, top decile and top 5%-tile of volatile stocks, where volatility is measured as the standard deviation of the past 12 months of daily excess returns. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009. Statistical significance is determined using Newey and West (1987) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994) automatic lag selection method to determine the lag length. The mean and standard deviation (in parentheses) for each variable is also provided. All coefficients are reported as effective annual rates.

	All			Excl Top Quintile			Excl Top Decile			Excl Top 5%-tile		
	I'	IV'	Mean (Std)	I'	IV'	Mean (Std)	I'	IV'	Mean (Std)	I'	IV'	Mean (Std)
Int	0.022	0.019		0.059	0.051		0.072	0.066		0.077	0.073	
	[0.91]	[0.80]		[2.35]	[1.96]		[2.87]	[2.56]		[3.26]	[2.95]	
β		-0.056	0.897		-0.008	0.797		-0.012	0.848		-0.017	0.873
		[2.61]	(0.967)		[0.37]	(0.851)		[0.52]	(0.910)		[0.83]	(0.939)
$\beta-$	-0.026		0.846	0.007		0.760	0.005		0.803	0.000		0.825
	[1.75]		-(0.228)	[0.46]		-(0.216)	[0.34]		-(0.223)	[0.02]		-(0.225)
$\beta+$	0.001		2.132	0.003		2.449	-0.002		2.286	-0.003		2.208
	[0.04]		(0.157)	[0.18]		(0.134)	[0.11]		(0.143)	[0.24]		(0.146)
BM	0.002	0.002	0.333	0.002	0.002	0.277	0.001	0.001	0.297	0.001	0.001	0.310
	[0.75]	[0.74]	-(0.126)	[1.03]	[0.99]	-(0.129)	[0.73]	[0.79]	-(0.129)	[0.41]	[0.47]	-(0.128)
Log-Size	-0.001	-0.001	2.222	0.000	0.000	2.272	0.000	0.000	2.267	-0.001	-0.001	2.256
	[1.83]	[1.79]	-(2.014)	[1.44]	[1.64]	-(1.913)	[1.76]	[1.81]	-(1.978)	[2.21]	[2.11]	-(2.004)
Past Ret	0.026	0.027	-3.815	0.055	0.056	-3.727	0.053	0.053	-3.778	0.057	0.058	-3.801
	[1.36]	[1.44]	(1.800)	[2.46]	[2.44]	(1.814)	[2.52]	[2.50]	(1.800)	[2.83]	[2.81]	(1.796)
Idio	0.078	0.129	0.518	-0.003	0.047	0.420	-0.069	-0.026	0.463	-0.072	-0.040	0.488
	[1.00]	[1.63]	(0.640)	[0.02]	[0.43]	(0.507)	[0.73]	[0.28]	(0.561)	[0.82]	[0.46]	(0.592)
Cosk	-0.101	-0.015	0.691	-0.067	-0.040	0.558	-0.072	-0.037	0.608	-0.064	-0.034	0.640
	[2.04]	[0.46]	(1.021)	[1.63]	[1.50]	(1.015)	[1.68]	[1.31]	(1.019)	[1.48]	[1.20]	(1.020)
Cokurt	0.009	0.033	55.730	-0.009	0.002	62.254	-0.008	0.002	58.729	-0.008	0.004	57.169
	[0.87]	[2.91]	(0.635)	[0.95]	[0.17]	(0.356)	[0.76]	[0.16]	(0.403)	[0.83]	[0.44]	(0.433)
$J^{Adj}-$		0.001	-5.705		0.001	-5.630		0.001	-5.673		0.002	-5.693
		[1.62]	(3.463)		[1.83]	(3.409)		[2.12]	(3.437)		[2.66]	(3.452)
$J^{Adj}+$		-0.004	5.432		-0.002	5.367		-0.002	5.390		-0.002	5.405
		[2.83]	(3.309)		[1.57]	(3.240)		[1.39]	(3.254)		[1.50]	(3.265)

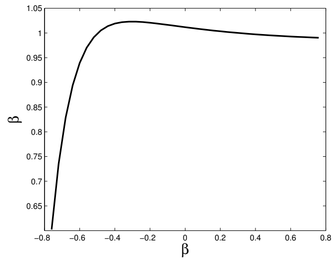


(a) Asymmetric Dependence (b) Symmetric Dependence

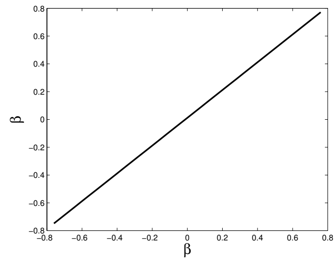
Fig. 1. Linear vs Asymmetric Dependence. Scatter plot of simulated bivariate data with asymmetric dependence (a) and symmetric dependence (b). The dependence between X and Y may be described by a linear component and a higher order reflecting differences in dependence across the joint return distribution. A joint distribution that displays larger dependence in one tail compared to the opposite tail is said to display asymmetric dependence.



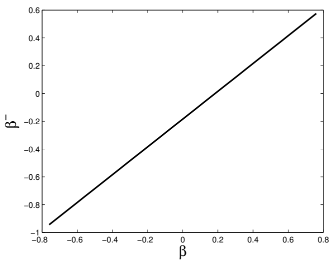
(a) CAPM Beta est's for $\alpha = 0$, $\beta \in (-0.75, 0.75)$.



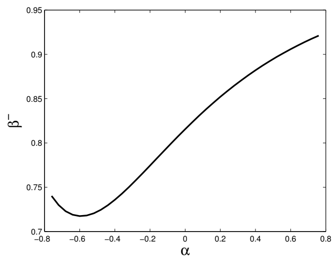
(b) CAPM Beta est's for $\beta = 1$, $\alpha \in (-0.75, 0.75)$.



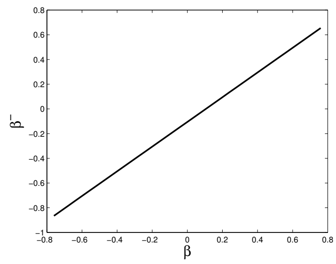
(c) CAPM Beta est's for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$.



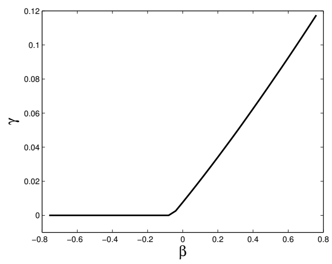
(d) Downside Beta est's for $\alpha = 0$, $\beta \in (-0.75, 0.75)$.



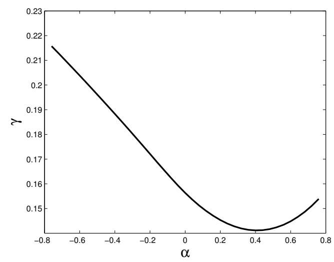
(e) Downside Beta est's for $\beta = 1$, $\alpha \in (-0.75, 0.75)$.



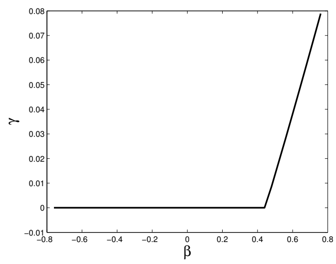
(f) Downside Beta est's for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$.



(g) Clayton copula parameter est's for $\alpha = 0$, $\beta \in (-0.75, 0.75)$.

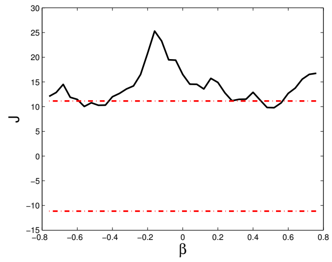


(h) Clayton copula parameter est's for $\beta = 1$, $\alpha \in (-0.75, 0.75)$.

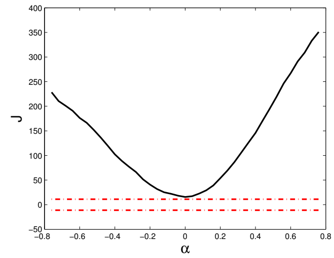


(i) Clayton copula parameter est's for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$.

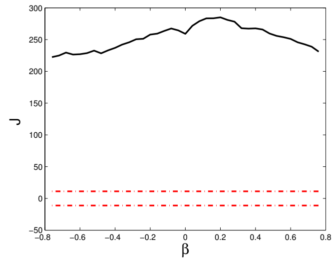
Fig. 2. Estimates of linear dependence and AD. We estimate the CAPM Beta, downside Beta and the Clayton copula parameter using $N = 10000$ simulated pairs of data (x, y), where $y_i = \beta x_i + \epsilon_i$, with $x_i \sim N(0.25, 0.15)$ and $\epsilon_i \sim N(0, (x_i + 0.25)^{\alpha})$. Higher levels of linear dependence are incorporated with higher values of β and higher levels of lower tail dependence are incorporated with higher levels of α. Figures (a), (d) and (g) provide estimates for varying levels of linear dependence but with no AD ($\alpha = 0$). Figures (b), (e) and (h) provide estimates for varying degrees of AD, with constant linear dependence ($\beta = 1$). Figures (c), (f) and (i) provide estimates for varying degrees of linear dependence, with constant AD ($\alpha = 0.5$).



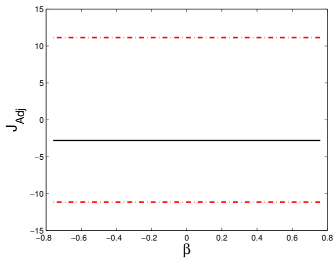
(a) J est's for $\alpha = 0$, $\beta \in (-0.75, 0.75)$.



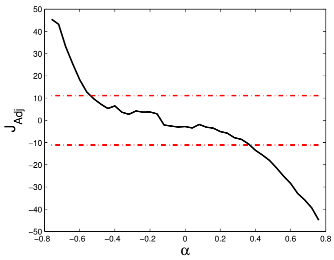
(b) J est's for $\beta = 1$, $\alpha \in (-0.75, 0.75)$.



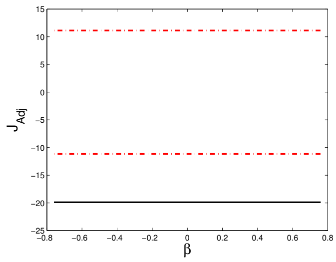
(c) J est's for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$.



(d) Adjusted J est's for $\alpha = 0$, $\beta \in (-0.75, 0.75)$.

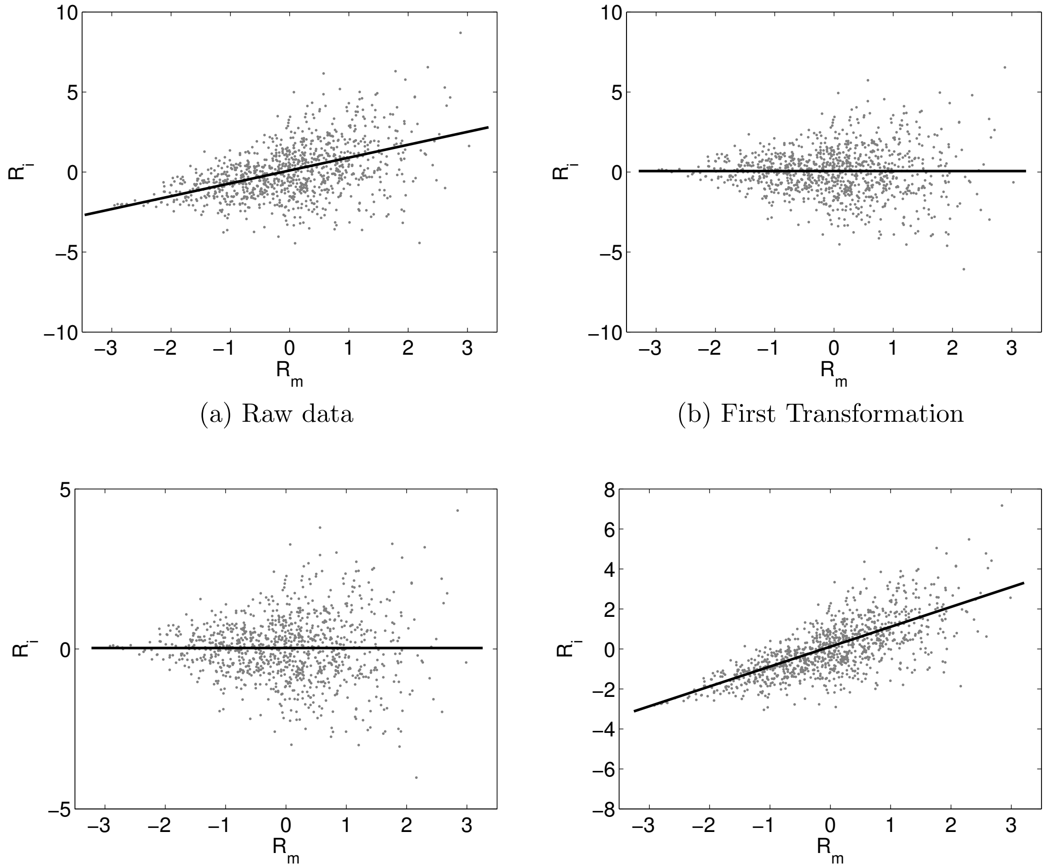


(e) Adjusted J est's for $\beta = 1$, $\alpha \in (-0.75, 0.75)$.



(f) Adjusted J est's for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$.

Fig. 3. Estimates of linear dependence and AD. We estimate the J statistic Hong, Tu, and Zhou (2006) and Adjusted-J statistic using $N = 10000$ simulated pairs of data (x, y), where $y_i = \beta x_i + \epsilon_i$, with $x_i \sim N(0.25, 0.15)$ and $\epsilon_i \sim N(0, (x_i + 0.25)^{\alpha})$. Higher levels of linear dependence are incorporated with higher values of β and higher levels of lower tail dependence are incorporated with higher levels of α. Figures (a) and (d) provide estimates for varying levels of linear dependence but with no AD ($\alpha = 0$). Figures (b) and (e) provide estimates for varying degrees of AD, with constant linear dependence ($\beta = 1$). Figures (c) and (f) provide estimates for varying degrees of linear dependence, with constant AD ($\alpha = 0.5$).



(a) Raw data

(b) First Transformation

(c) Standardization

(d) Second Transformation

Fig. 4. J^{Adj} Data Transformations. To calculated J^{Adj}, statistic, we first take random samples, $\{R_{it}, R_{mt}\}_{t=1}^{T}$, as in (a) and let $\hat{R}_{it} = R_{it} - \beta R_{mt}$ where R_{it} is the continuously compounded return on the i^{th} asset, R_{mt} is the continuously compounded return on the market and $\beta = \text{cov}(R_{it}, R_{mt})/\sigma^2_{R_{mt}}$. This transformation forces $\beta_{\hat{R}_{it},R_{mt}} = 0$, as in (b). We standardize the transformed data yielding R^S_{mt} and $\hat{R}^S_{it}$ in (c). Finally, were-transform the data to have $\hat{\beta} = 1$ by letting $\tilde{R}_{mt} = R^S_{mt}$ and $\tilde{R}_{it} = \hat{R}^S_{it} + R^S_{mt}$ in (d). The solid line through the middle of each plot is given to illustrate how the linear trend changes with each transformation.

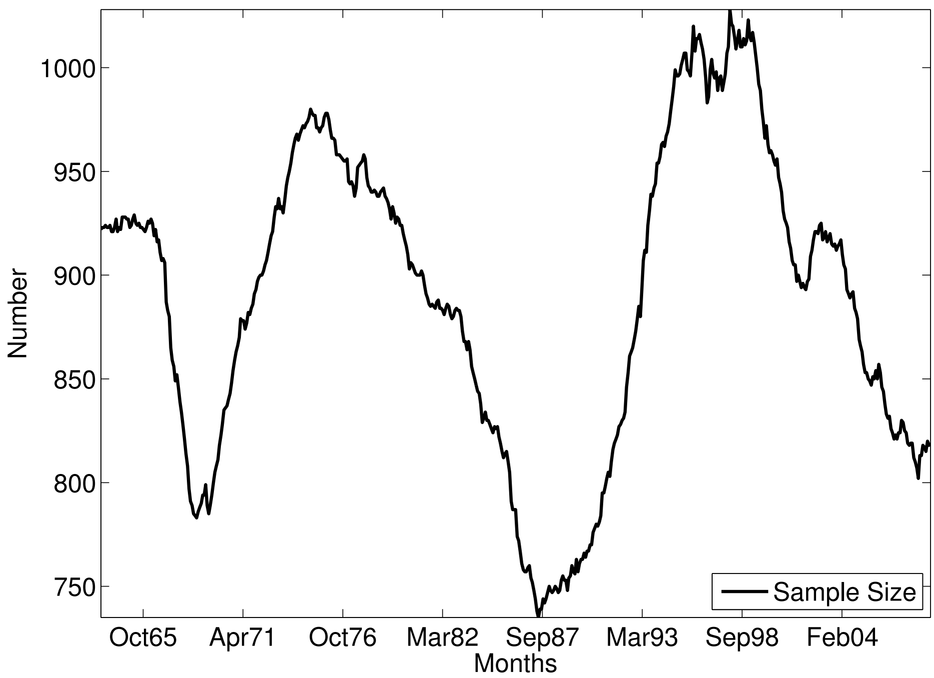
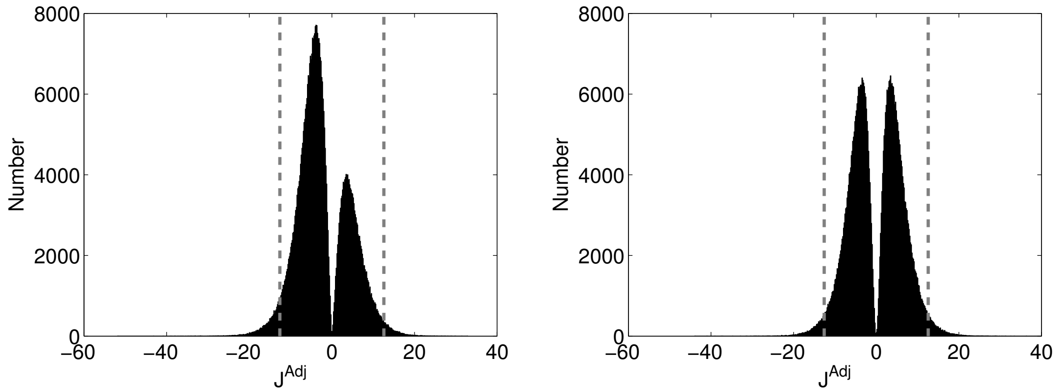


Fig. 5. Our monthly sample size. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009.



(a) Actual Distribution (b) Distribution Under Normality

Fig. 6. Actual and Hypothetical Distribution of the J^{Adj}. We focus on stocks listed on the NYSE between July 1963 and December 2009. At a given month, t, we estimate J^{Adj} using the next 12 months of daily excess return data. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. The histogram of all J^{Adj} observations is presented in (a). We include the distribution of the J^{Adj} computed using simulated multivariate normal data, parameterized at each month in (b). The size of each sample is chosen to match the number of days in each 12 month period. The vertical lines represent 95% cut-offs following a χ^2_6 distribution. A positive (negative) J^{Adj} is indicative of excess upside (downside) risk over and above the tail risk implied by ordinary β.

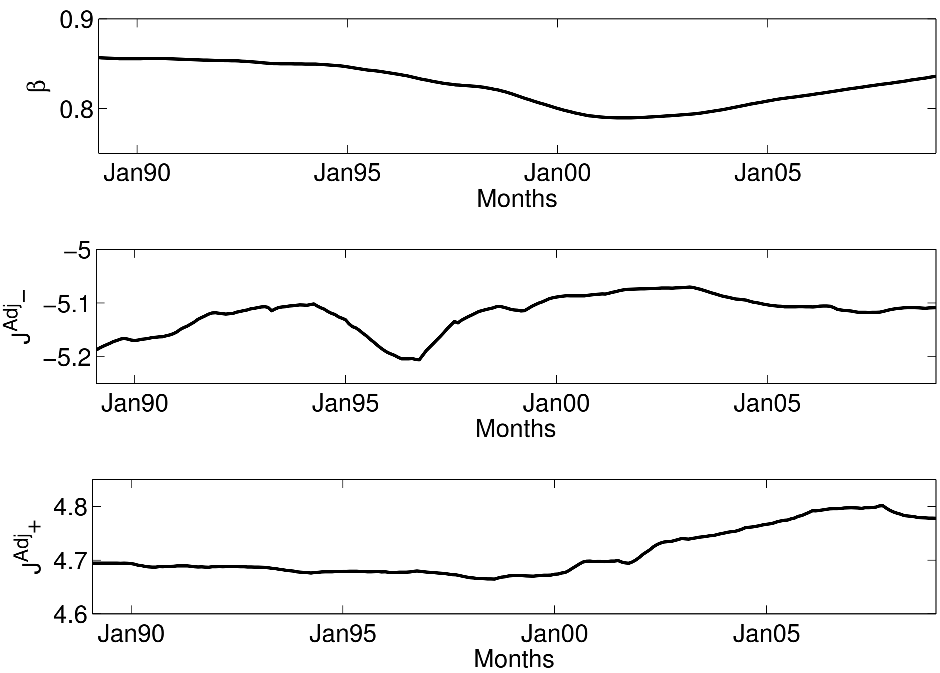


Fig. 7. This figure depicts the median factor loading for β, $J^{Adj}-$ and $J^{Adj}+$ at a given month, t, between January 1989 and January 2009 using the next 12 months of daily excess returns. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. The estimate is calculated using all historical data up to and including time t.

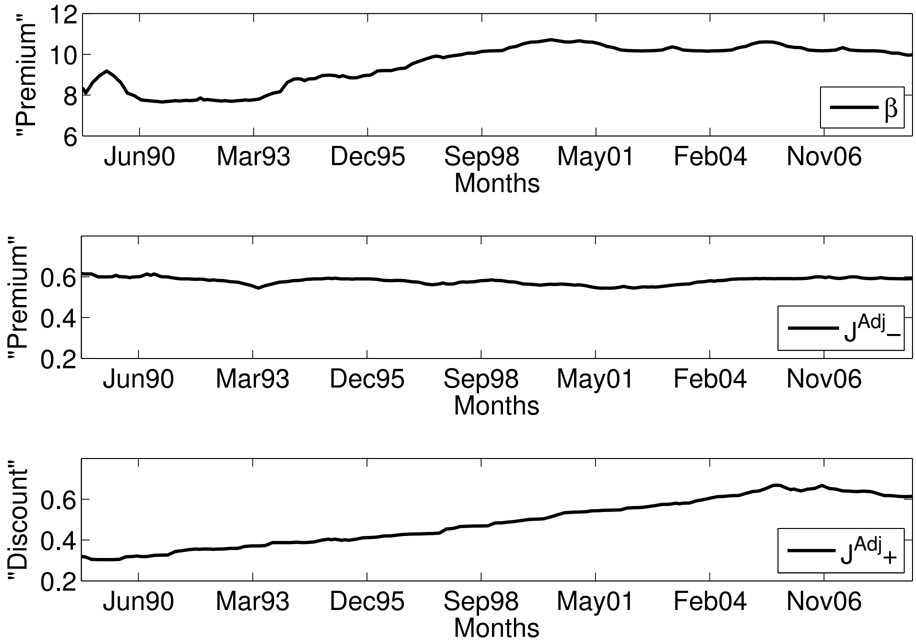


Fig. 8. This figure depicts the factor sensitivity using the Fama and MacBeth (1973) asset pricing procedure where cross-sectional regressions are computed every month rolling forward. At a given month, t, the average of the next 12 excess monthly returns is regressed against β, idiosyncratic risk, coskewness, cokurtosis, $J^{Adj}-$ and $J^{Adj}+$ estimated using the next 12 months of daily excess return data, and size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret"), computed as at time t. We proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. We restrict our attention to stocks listed on the NYSE between July 1963 and December 2009. The "Premium" for β and for $J^{Adj}-$ and the "Discount" for $J^{Adj}+$ between January 1989 and January 2009 is given by the time series median factor sensitivity using all historical sensitivity estimates up to and including time t.