# The rising importance of Asymmetric Dependence in UK equity returns 

Jamie Alcock ${ }^{\text {a }}$, Petra Andrlikova*a<br>${ }^{a}$ The University of Sydney Business School, Sydney, Australia


#### Abstract

UK listed equity returns exhibit asymmetric dependence. This asymmetric dependence is priced in the cross section independently of linear market ( $\beta$ ) risk. In our sample, average levels of lower-tail asymmetric dependence attract a premium of $6.9 \%$ per annum and average levels of upper-tail dependence yield a discount of $7.4 \%$ p.a. The $\beta$ market risk is insignificant in the UK listed equities. Whilst the degree of upper-tail and lower-tail dependence has been decreasing over the past fifteen years, the market price of both lower-tail asymmetric dependence and upper-tail asymmetric dependence has been increasing markedly through time.

Keywords: Asymmetric dependence, asset pricing, tail risk, downside risk, $\beta$, $J^{A d j}$

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## 1. Introduction

Asymmetric dependence (AD) describes a characteristic of the joint distribution of returns whereby the dependence between a stock and the market during market downturns differs from that observed during market upturns. Investors may well exhibit preferences for certain types of AD. For example, consider two stocks $A$ and $B$ that have identical $\beta$ and equal average returns. Stock $A$ exhibits a higher correlation in the lower tail of excess returns (Figure 1a) whilst stock $B$ is symmetric in return dependence (Figure 1b). Under the assumptions of the Sharpe-Lintner CAPM, investors will be indifferent to the choice between stocks A and B as the expected returns on both stocks, as well as their $\beta \mathrm{s}$, are equal. However, investors may prefer stock $B$ over $A$ since stock $A$ is more likely to suffer abnormal losses during any market downturn. If investors exhibit preferences with respect to AD then we expect AD to be priced in financial markets if, in addition, it exists and is non-diversifiable. Disappointment-averse investors with state-dependent preferences, such as those described by Skiadas (1997), will demand a return premium to compensate for lower-tail asymmetric dependence exposure. The primary aim of this paper is to identify and quantify the price of AD in UK listed equities.

Many authors find evidence for the existence of AD in US stock equities (Alcock and Hatherley, 2016; Bali, Demirtas, and Levy, 2009; Bollerslev and Todorov, 2011; Hong, Tu, and Zhou, 2007; Ang, Chen, and Xing, 2006; Post and Van Vliet, 2006; Hartmann, Straetmans, and De Vries, 2004; Patton, 2004; Ang and Bekaert, 2002; Ang and Chen, 2002; Longin and Solnik, 2001; Erb, Harvey, and Viskanta, 1994). In addition, several of these studies identify the existence of AD between welldiversified stock indices, thereby providing credible evidence that AD is not easily diversified (Hong, Tu, and Zhou, 2007; Hartmann, Straetmans, and De Vries, 2004; Patton, 2004; Ang and Bekaert, 2002; Longin and Solnik, 2001; Erb, Harvey, and Viskanta, 1994).

The identification of AD amongst UK listed equities is more limited with the notable exceptions of Knight, Satchell, and Tran (1995); Knight, Lizieri, and Satchell (2005); Ning (2010). Many of these previous studies have explored dependence us-
ing a single measure, thereby capturing both the symmetric, linear dependence and AD with the same metric. From an asset pricing perspective, it is important to separate these factors to identify the price of AD orthogonally to the price of linear, market ( $\beta$ ) risk.

We employ the adjusted $J$-statistic (Alcock and Hatherley, 2016; Ang et al., 2006) to determine the asymmetric dependence between the returns of each equity and the market separately from the $\beta$ of each equity stock. Using this metric, we find that the asymmetric dependence is significantly priced in the cross section of UK stock returns. In our sample, average levels of lower-tail dependence attract a premium of $6.9 \%$ per annum and average levels of upper-tail dependence yield a discount of $7.4 \%$ p.a. The $\beta$ market risk is insignificant.

Under a multi-asset pricing framework, non-linear premia imply that the benchmark portfolio is spanned by $\beta$, representing the linear component of dependence between stock returns and the market proxy, and a higher order component of dependence. When the higher order component of dependence is characterised by increased correlation in up or down markets, the price of an asset in an economy containing investors with state-dependent preferences will be contingent upon the state of the market. Consequently, the dependence between the rate of return on an investment and the market will also be contingent on the state of the market.

The main objective of this paper is to examine whether AD, and lower-tail dependence (LTAD) and upper-tail dependence (UTAD) in particular, attract a premium independent of the premium attached to $\beta$. However, we contribute to the existing literature in several ways, described as follows. First, we quantify the level of AD for UK equity returns independently of linear market risk. Second, we find that this asymmetric dependence is priced in the cross section. Third, we quantify the price of UTAD and LTAD separately (and independently of $\beta$ ). Fourth, we find that the existence of AD predicts returns up to fifteen months in advance. Fifth, we find that both the level and price of AD has changed over time. The degree of UTAD and LTAD has decreased over the past fifteen years. Both LTAD and UTAD have become more heavily priced over time.

We proceed as follows. In Section 2, we explore the theoretical justification of
investor preferences for asymmetric dependence. In Section 3, we describe how we measure AD independently of market $\beta$. In Section 4, we describe the data and methods used to price AD in UK listed equities. We present out results in Section 5 and conclude in Section 6.

## 2. Asymmetric Dependence and Disappointment

Ang et al. (2006) argue that the existence of a downside risk premium is consistent with an economy of investors that are averse to disappointment in the framework developed by Gul (1991). This framework deviates from the expected utility paradigm upon which traditional asset pricing theory is built via the assumption that the desirability of an act in a given state depends on not only the objective payoff associated with the act, but also the state itself. This results in a one parameter extension of the expected utility framework whereby outcomes that lie above an endogenously defined reference point (elating outcomes) are downweighted relative to outcomes that lie below the reference point (disappointing outcomes). The disappointment-averse utility function is therefore defined as:

$$
\phi(x, \nu)= \begin{cases}u(x) & \text { for } x \text { satisfying } u(x) \leq \nu  \tag{1}\\ \frac{u(x)+\beta \nu}{1+\beta} & \text { for } x \text { satisfying } u(x)>\nu\end{cases}
$$

where $u$ is a generic utility function, $\beta$ is the coefficient of disappointment aversion, and $\nu$ is the certainty equivalent satisfying $\sum_{x} \phi(x, \nu) p(x)=\nu$ for probability function $p(x)$. This function inexplicably ties an agent's risk aversion to their aversion to disappointment and therefore cannot accommodate the separation of dependence driven tail risk from systematic risk ${ }^{2}$.

[^1]An alternative framework is considered by Skiadas (1997) in which subjective consequences (disappointment, elation, regret, etc) are incorporated indirectly through the properties of the decision maker's preferences rather than through explicit inclusion among the formal primitives. For example, if an act $y$ is considered ex ante to yield better consequences than $x$ overall, then the subjective feeling of disappointment in having chosen $y$ over $x$ in the event that $F$ occurs can lead to the situation in which $x$ is no less desirable than $y$ during event $F$. In this case, an aversion to disappointment implies that $x$ is preferred over $y$ in the event that $F$ occurs. This is formally written as:

$$
\begin{equation*}
\left(x=y \text { on } F \text { and } y \succeq^{\Omega} x\right) \Rightarrow x \succeq^{F} y, \quad x, y \in X \tag{2}
\end{equation*}
$$

where $\Omega$ represents the set of all events, $X$ is the set of acts, and $\succeq$ defines a complete and transitive preference order. Disappointment is therefore defined by the agent's preference relation rather than if an outcome is worse than a certainty equivalent.

Individuals with Skiadas (1997) preferences are therefore endowed with a family of conditional preference relations, one for each event (Grant et al., 2001). Preferences are state-dependent, as in the Gul (1991) framework, and because consequences are treated implicitly through the agents preference relations, preferences can be regarded as "non-separable" in that the ranking of an act given an event may depend on subjective consequences of these acts outside of the event.

Equation (2) has two important implications for our study. First, the outcomes associated with $x$ and $y$ given $F$ need not be bad outcomes. This implies that the market may display feelings of disappointment even in the absence of poor market conditions leading to the expectation of time varying tail risk premia. Second, the separation of systematic risk from excess tail risk follows directly from (2) in that an act $y$ may be preferred over $x$ overall given the global risk aversion properties of the individual, but may be more or less appealing during a particular event as a result of the markets attitude towards disappointment and elation. We therefore
the existence of counter-cyclical risk aversion (Epstein and Zin, 2001; Routledge and Zin, 2010) due to the constancy of the downside aversion parameter across states.
expect the market to assign a separate premium to both global (systematic) risk aversion and aversion to AD.

Although disappointment aversion reflects a divergence from von Neumann Morgenstern expected utility theory, the validity of a market price of risk continues to hold as a result of the relationship between disappointment aversion and risk aversion. Gul (1991), for example, demonstrates that risk aversion implies disappointment aversion. Conversely, Routledge and Zin (2010) argue that investor preferences exhibit more risk aversion as the penalty for disappointing outcomes increases, effectively as a result of an increase in the concavity of the utility function. This implies that an increase in downside risk is also likely to be captured by an increase in systematic risk.

From a risk management perspective, this induces a substitution effect between risk aversion and disappointment aversion in that the effect of risk aversion on a utility maximizing hedge portfolio decreases as disappointment aversion increases, and vice versa (Lien and Wang, 2002).

In an economy consisting of investors that are averse to disappointment in the framework developed by Gul (1991), Ang et al. (2006) show that investors require higher compensation to invest in stocks that are sensitive to market downturns.

## 3. Measuring Asymmetric Dependence

Various authors have proposed a range of measures to capture AD and/or tail risk including downside $\beta$ (Ang et al., 2006), Archimedian copula (Genest, Gendron, and Bourdeau-Brien, 2009), $H$-statistic (Ang and Chen, 2002) and the original version of $J$-statistic (Hong et al., 2007). Alcock and Hatherley (2016) note that most of these statistics are unsuitable for asset pricing purposes for various reasons, including non-monotonicity between the metric and AD and nonorthogonality between the metric and $\beta$. Alcock and Hatherley (2016) propose an adjustment to the $J$-statistic of Hong et al. (2007) that generates a monotonic measure that is orthogonal to CAPM $\beta$ and so allows for the pricing of AD independently of the price of $\beta$ risk.

The Alcock and Hatherley (2016) Adjusted $J$-statistic ( $J^{\text {Adj }}$ ) is defined by the
following procedure. We unitise $\beta$ in each data set before the $J$-statistic is estimated. That is for each set $\left\{R_{i t}, R_{m t}\right\}_{t=1}^{T}$, we get $\hat{R}_{i t}=R_{i t}-\beta R_{m t}$, where $R_{i t}$ and $R_{m t}$ is continuously compounded return on asset $i$ and market, and $\beta=\operatorname{cov}\left(R_{i t}, R_{m t}\right) / \sigma_{R_{m t}}^{2}$. The first transformation implies that $\beta_{\hat{R}_{i t}, R_{m t}}=0$. This enables us to standardise the data to get identical standard deviation of the CAPM regression residuals and get $R_{m t}^{S}$ and $\hat{R}_{i t}^{S}$. The final transformation step sets the $\hat{\beta}$ to 1 by letting $\tilde{R}_{m t}=R_{m t}^{S}$ and $\tilde{R}_{i t}=\hat{R}_{i t}^{S}+R_{m t}^{S}$. After this transformation, all data sets have the same $\beta$ and standard deviation of model residuals, which compels the $J$-statistic to be invariant to the linear dependence and the level of idiosyncratic risk.

The Adjusted $J$-statistic $\left(J^{\text {Adj }}\right)$ is then defined as

$$
\begin{equation*}
J^{A d j}=\left[\operatorname{sgn}\left(\left[\tilde{\rho}^{+}-\tilde{\rho}^{-}\right] \mathbf{1}\right)\right] T\left(\tilde{\rho}^{+}-\tilde{\rho}^{-}\right)^{\prime} \hat{\Omega}^{-1}\left(\tilde{\rho}^{+}-\tilde{\rho}^{-}\right), \tag{3}
\end{equation*}
$$

where $\tilde{\rho}^{+}=\left\{\tilde{\rho}^{+}\left(\delta_{1}\right), \tilde{\rho}^{+}\left(\delta_{2}\right), \ldots, \tilde{\rho}^{+}\left(\delta_{N}\right)\right\}$ ans $\tilde{\rho}^{-}=\left\{\tilde{\rho}^{-}\left(\delta_{1}\right), \tilde{\rho}^{-}\left(\delta_{2}\right), \ldots, \tilde{\rho}^{-}\left(\delta_{N}\right)\right\}, \mathbf{1}$ is $N \times 1$ vector of ones, $\hat{\Omega}$ is an estimate of the variance-covariance matrix, (Hong et al., 2007). The correlations are defined as

$$
\begin{gather*}
\tilde{\rho}^{+}=\operatorname{corr}\left(\tilde{R}_{m t}, \tilde{R}_{i t} \mid \tilde{R}_{m t}>\delta, \tilde{R}_{i t}>\delta\right)  \tag{4}\\
\tilde{\rho}^{-}=\operatorname{corr}\left(\tilde{R}_{m t}, \tilde{R}_{i t} \mid \tilde{R}_{m t}<-\delta, \tilde{R}_{i t}<-\delta\right) . \tag{5}
\end{gather*}
$$

Hong et al. (2007) show that $\left|J^{A d j}\right| \sim \chi_{N}^{2}$. With symmetric dependence the value of $J^{\text {Adj }}$ will be close to zero. A significant and non-zero value of $J_{\text {Adj }}$ provides an evidence of asymmetry between the lower and upper-tail dependence. A positive value of $J^{A d j}$ indicates upper-tail asymmetric dependence. A negative value of $J^{A d j}$ indicates lower-tail asymmetric dependence.

Consistent with Alcock and Hatherley (2016), we separate the UTAD and LTAD by creating $J^{A d j}+$ and $J^{A d j}-$ using indicator function $\mathbb{I}_{c}$, which takes value of 1 when condition $c$ is satisfied and zero otherwise.

$$
\begin{align*}
& J^{A d j}+=J^{A d j} \mathbb{I}_{J^{A d j}>0}  \tag{6}\\
& J^{A d j}-=J^{A d j} \mathbb{I}_{J^{A d j}<0} \tag{7}
\end{align*}
$$

$J^{A d j}$ is a non-parametric measure of asymmetric dependence and separates the tail dependence from non-normal characteristics of returns (Alcock and Hatherley, 2016). It does not require multivariate normal assumptions, consistent with the recommendation of Stapleton and Subrahmanyam (1983) and Kwon (1985). Adjusting the $J$-statistic developed by Hong et al. (2007) forces the standard deviation of model residuals to be identical for all data sets, which allows us to separate the downside risk from other firm specific risk. The idiosyncratic risk is priced when investors do not hold sufficiently diversified portfolios (Fu, 2009; Campbell, Lettau, Malkiel, and Xu, 2001; Merton, 1987). We control for idiosyncratic risk.

The estimated tail risk is based on relatively small number of positive or negative joint returns. Any measure of asymmetric dependence will suffer from high likelihood of Type II error. Consequently, our findings are conservative estimates.

## 4. Data and Empirical Design

We explore the price of AD using the continuously compounded daily returns of all UK equities from the beginning of data recorded for UK (1 January 1987) until 29 May 2015. We retrieve daily stock price information from WRDS Compustat Global Security Daily database. In particular, we get a time series of daily firm identifier (gvkey), date, close price (prccd) and number of shares (cshoc). We collect annual balance sheet information from WRDS Compustat Global Fundamentals Annual database. We collect firm identifier (gvkey), financial year (fyear), total asset value (at), common equity (ceq) for all UK listed equities. We use the daily UK 3-month Treasury bill rate as a proxy for the risk free rate and the FTSE100 index return as a proxy for market return. The daily observations on UK 3-month Treasury bill rate and FTSE100 index are collected from DataStream.

We define the product of the daily close price and number of shares to be firm market value (MV) an the ratio between the common equity and firm market value to be the book-to-market ratio (BM). We exclude all daily returns with negative BM and BM greater than 1,000 to cover for potential data errors. We also apply a liquidity rule and remove stock return time series with more than $30 \%$ of zero or missing daily returns. For each month $t$, only stock return time series with data
available in months $t-12$ to $t+12$ are included in the final data set. Our final sample comprises 1,239 distinct firms with 3,702,201 of firm-return observations.

For a given month $t$, the $J^{A d j}$-statistic is computed using daily excess returns from the next 12 months following the definition from equation (3) and using the following levels of exceedances $\delta=\{0,0.2,0.2,0.6,0.8,1\}$, consistent with Hong et al. (2007) and Alcock and Hatherley (2016). The CAPM $\beta$ is estimated using the next 12 months of daily excess returns.

We follow Alcock and Hatherley (2016) and Ang et al. (2006) to provide evidence of downside risk premium on the cross section of UK stock returns. We first look at the contemporaneous relation between asymmetric dependence and returns, whilst controlling for factors of controlling for systematic risk as well as controlling for size, book-to-market ratio, average excess monthly return from past 12 months, idiosyncratic risk, coskewness and cokurtosis. The contemporaneous method is used to avoid the errors-in-variables problem (Kim, 1995).

At each month $t$, the average of the next 12 monthly excess returns is regressed against the $J^{A d j}$, CAPM $\beta$, upside and downside $\beta$, idiosyncratic risk, size, book-to-market ratio, coskewness and cokurtosis estimated using daily returns from the same 12 -month period and the average of past 12 monthly excess returns. Regressors are Winsorised at the $1 \%$ and $99 \%$ level each month to control for inefficient factor estimates. We use data on daily basis to ensure sufficient number of observations for the downside risk measure. The risk factors estimated using daily data are likely to be noisy relative to lower frequency data, the tests of significance should however have sufficient power because they are computed on a relatively long history of data (Lewellen and Nagel, 2006).

We calculate the control variables for a given month, $t$, in the following manner. The downside $\beta$, upside $\beta$, coskewness, cokurtosis are estimated using the next 12 months of excess daily returns. The downside and upside $\beta$ are defined as $\beta^{-}=\operatorname{cov}\left(R_{i}, R_{m} \mid R_{m}<0\right) /\left(\operatorname{var}\left(R_{m} \mid R_{m}<0\right)\right.$ and $\beta^{+}=\operatorname{cov}\left(R_{i}, R_{m} \mid R_{m}>\right.$ $0) /\left(\operatorname{var}\left(R_{m} \mid R_{m}>0\right)\right.$, where $R_{i}$ is the excess return on asset $i$ and $R_{m}$ is the market excess return. Firm size is the average of the log value of market value calculated over the next 12 months of daily observations. The book-to-market ratio
is the average BM from the next 12 months of daily observations. The idiosyncratic risk is measured as the standard deviation of CAPM residuals estimated using daily excess returns from the next 12 months. Monthly excess returns are calculated from the continuously compounded excess daily returns. We use daily risk-free rate to obtain the excess returns.

The risk premia for each factor is estimated using the Ang et al. (2006) procedure where cross-sectional regressions are computed every month rolling forward using a 12 month window to estimate the relevant factors. We use the Newey and West (1987) method to test for statistical significance with overlapping data and Newey and West (1994) for automatic lag selection. We use a short-rolling window to account for time variation in systematic risk (Bollerslev, Engle, and Wooldridge, 1988; Bos and Newbold, 1984; Fabozzi and Francis, 1978; Ferson and Harvey, 1991, 1993; Ferson and Korajczyk, 1995) and variations in downside risk (Alcock and Hatherley, 2016).

## 5. Asymmetric Dependence Risk Premium

## Factor Correlations

The correlation between the $J^{A d j}$ and other factors is described in Table 1. The $J^{A d j}$ is largely uncorrelated with any other factor (except coskewness). The $J^{A d j}$ is uncorrelated with the CAPM beta, consistent with the design and construction of the $J^{A d j}$ metric. This empirically confirms that the $J^{A d j}$ provides an AD measure that is orthogonal to $\beta$. The $J^{\text {Adj }}$ is uncorrelated with the downside and upside $\beta$, which is not unexpected as the $J^{A d j}$-statistic is constructed to be $\beta$-invariant. The $J^{A d j}$ is most highly correlated with coskewness with a correlation coefficient 0.399. This is also unsurprising as the $J^{A d j}$ is the aggregate of the economically meaningful higher order terms in the Edgeworth series expansion of the excessreturn distribution, whereas the coskewness is but one of these terms.

Excess returns are more highly correlated with $J^{\text {Adj }}$ than with any other considered risk factor. The negative sign $(-0.254)$ suggests that the greater the LTAD (UTAD) the higher (lower) the excess return. In the UK equity market, the downside and upside $\beta$ are poorly correlated with returns, which is in contrast with

Ang et al. (2006) findings in the US market.
[TABLE 1 ABOUT HERE]
We use the double-sorting method (Fama and French, 1992) to examine the downside $\beta$-return relation relative to the $\beta$-return relation. We sort stocks into $\beta$ deciles and then into downside $\beta$ decile within each $\beta$ decile at each month between January 1987 and May 2015. The equally weighted average returns in the portfolios sorted by $\beta$ and downside $\beta$ are presented in Panel A of Table 2. The differences in returns suggest that after controlling for $\beta$, the downside $\beta$ does not contain relevant information explaining return variation in UK listed stocks.
[TABLE 2 ABOUT HERE]
We apply the same double-sort procedure using the $J^{\text {Adj }}$ deciles and sort them into $\beta$, size and coskewness deciles. After controlling for market risk $(\beta)$, we find a positive relationship between AD and returns across all $\beta$ deciles (Panel B of Table 2). We also find a positive ${ }^{3}$ relation between AD and excess returns across all size deciles (Panel C of Table 2) and coskewness deciles (Panel D of Table 2).

## The Price of Asymmetric Dependence

The distribution of $J^{A d j}$ is asymmetric around zero with LTAD being more frequently observed than UTAD ( $69 \%$ vs. $31 \%$ ). The $J^{\text {Adj }}$ calculated using UK stocks is more asymmetrically distributed than the $J^{A d j}$ estimated on US stocks (Alcock and Hatherley, 2016) suggesting that LTAD is more prevalent in the UK market than in the US market. In the context of Bekaert and Wu (2000) it appears that the asymmetric effects of news on conditional covariance between stock and market returns is greater in the UK than in the US.
[FIGURE 2 ABOUT HERE]

[^2]We estimate the risk premia attached to $J^{A d j}$ and other control variables in the value-weighted regressions using the Ang et al. (2006) coincident-return method (Regressions I to V from Table 3). As a contrast, we regress excess returns on $\beta$ and other risk factors without including the AD measure in Regression I and II from Table 3. When the $J^{A d j}$ is not included Size, BM and Idiosyncratic risk are significantly priced in excess returns of UK listed equities. In the absence of $J^{A d j}$, the market risk premium is insignificant in the UK stock market. The downside $\beta$ is not significant in explaining excess returns (Regressions II from Table 3), which is consistent with our results from the double-sort procedure. The upside $\beta$ on the other hand turns out to be significant.

## [TABLE 3 ABOUT HERE]

When we include $J^{A d j}$ into Regression III from Table 3, we find that AD is significantly priced in excess returns of UK listed equities. The t-statistic attached to the $J^{A d j}$ is 5.812 , which not only exceeds the usual level of 1.96 but also exceeds the Harvey et al. (2014) level of $3.0^{4}$. The "typical premium" that we define to be the product of the average factor value multiplied by the factor premium is $(-2.336 \times-0.011)=2.570 \%$. The negative coefficient of $J^{\text {Adj }}(-0.011)$ implies that higher levels of AD lead to a decrease in excess return.

One explanation for the negative coefficient of $J^{\text {Adj }}$ is that LTAD is associated with a premium and UTAD attracts a discount. We quantify the price of LTAD and UTAD separately by regressing excess returns against the $J^{A d j}-$ and $J^{A d j}+$ defined in equations (6) and (7). We present these results in Regression IV and V from Table 3. The premium (discount) associated with a one-unit increase in LTAD (UTAD) is $1.1 \%$ ( $1.2 \%$ ). The "typical premium" associated with LTAD is $6.9 \%$, whereas the "typical discount" related to UTAD is $7.4 \%$. The market price of risk is insignificant in the cross section of UK listed equities. These results remain largely unchanged after controlling for downside and upside $\beta$ in Regression V. Most of

[^3]the control covariates coefficients remain qualitatively robust to the inclusion of $J^{A d j}$, except for Coskewness. The Coskewness changes from insignificant, when the $J^{A d j}$ is not included, to significant and positive, when the $J^{A d j}$ is included.
[FIGURE 3 ABOUT HERE]
We also explore the variation of AD risk premium in time. We re-estimate the regression model IV from Table 3 using the Ang et al. (2006) coincident-return procedure at each month between June 1992 and June 2014, using only historical data available to the investor at that month. 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 compute the factor premia using medians to capture the trend in risk premium over time rather than an accurate portrayal of the compensation for risk. The development of factor loadings through time is illustrated in Figure 3. The time variations of risk premia attached to $\beta, J^{\text {Adj }}-$ and $J^{A d j}+$ are illustrated in Figure 4.

## [FIGURE 4 ABOUT HERE]

The degree of LTAD and UTAD is decreasing through time. Both LTAD and UTAD have become more heavily priced and more highly valued by investors. The median $\beta$ is increasing in time. The premium for market risk remains insignificant through time however.
[TABLE 4 ABOUT HERE]
We also test the ability of $J^{\text {Adj }}$ to predict future returns using the standard Fama and MacBeth (1973) procedure. As well as being a good robustness test, this also provides an insight into whether an investor can extract information about future returns from AD measures. In Table 4, we repeat Regressions III and IV from Table 3 using 1 month, 3 month, 6 month, 9 month, 12 month and 15 month future excess returns as the dependent variable. The typical level of AD can explain 250 bp of future one month excess return. This compares with 590 bp explained by the typical level of $\beta$. The $J^{A d j}$ is significant in predicting
future returns up to fifteen months in advance. Using our definition of the typical premium, we find that the $J^{A d j}$ is more influential in predicting future returns than any other significant factor considered except $\beta$ and idiosyncratic risk.

## Robustness of Results

We test the robustness of our results by exploring the regression under a variety of different assumptions. In Table 5 in Appendix, we present the results using the equally-weighted Ang et al. (2006) coincident-return method. In Table 6 in Appendix, we test the robustness of our predictive regressions findings by excluding the most volatile stocks. The volatility is measured as the standard deviation of the past 12 months of daily excess returns. We exclude the year 1987 from our observations and report our regression results in Table 7 in Appendix. Our findings are qualitatively similar across all model specifications.

## 6. Conclusion

We find evidence of asymmetric dependence in returns of UK listed equities. Lower-tail asymmetric dependence occurs more frequently than upper-tail dependence. This AD is priced in the cross section of stock returns. Using the $\beta$-invariant measure of AD developed by Alcock and Hatherley (2016) we show that in our sample, LTAD (UTAD) is associated with $6.9 \%$ ( $7.4 \%$ ) premium (discount). The market risk premium is insignificant in the UK stock market. The degree of uppertail and lower-tail dependence has been decreasing over the past fifteen years. The price of lower-tail dependence and upper-tail dependence has increased over time. Our results imply that important price information is contained within the relative magnitude of UTAD and LTAD as well as within the linear relationship between asset returns.

Our key findings have important implications not only for asset pricing, but also for cost of capital, internal capital allocation, strategic asset allocation, financial risk management, portfolio management and portfolio performance assessment. Diversified-asset managers can use AD information in internal planning. For example, in a firm with LTAD, the cost of capital without including the price of

AD would be substantially underestimated. The AD information may help managers to estimate the expected return on capital and increase the efficiency of their project management and capital allocation.

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## Tables and Figures

## Factor Correlation

Table 1: This table presents the correlation between each factor. We restrict our attention to UK stocks listed between January 1987 and May 2015. At each month, $t$, we estimate $\beta$, $\beta^{-}$, $\beta^{+}$, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and $J^{\text {Adj }}$ 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 FTSE 100 index and the risk free rate with the 3-month UK Treasury Bill rate. All factors are Winsorised at the $1 \%$ and $99 \%$ level at each month.

|  | $\beta$ | $\beta^{-}$ | $\beta^{+}$ | Log-size | BM | Past Ret | Idio | Cosk | Cokurt | $J^{\text {Add }}$ | Ret |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\beta$ | 1 | 0.747 | 0.784 | 0.409 | -0.084 | -0.012 | 0.124 | 0.109 | 0.569 | 0.120 | -0.098 |
| $\beta^{-}$ |  | 1 | 0.488 | 0.232 | -0.084 | 0.015 | 0.123 | -0.225 | 0.447 | -0.052 | -0.058 |
| $\beta^{+}$ |  |  | 1 | 0.383 | -0.060 | -0.014 | 0.041 | 0.364 | 0.523 | 0.191 | -0.059 |
| Log-size |  |  |  | 1 | -0.141 | 0.044 | -0.095 | 0.112 | 0.290 | 0.085 | -0.037 |
| BM |  |  |  |  | 1 | -0.026 | -0.052 | -0.006 | -0.017 | 0.016 | -0.008 |
| Past ret |  |  |  |  |  | 1 | -0.153 | -0.084 | 0.035 | -0.028 | -0.021 |
| Idio |  |  |  |  |  |  | 1 | 0.125 | -0.294 | 0.158 | -0.346 |
| Cosk |  |  |  |  |  |  | 1 | 0.132 | 0.399 | -0.056 |  |
| Cokurt |  |  |  |  |  |  |  | 1 | 0.122 | -0.005 |  |
| $J^{\text {Adj }}$ |  |  |  |  |  |  |  |  | 1 | -0.254 |  |
| Ret |  |  |  |  |  |  |  |  | 1 |  |  |

## The Time Series Average Returns for Double Sorted Portfolios

Table 2: For a given month, we first sort stocks into $\beta$ deciles, and then into $\beta^{-}$or $J^{\text {Adj }}$ 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 $J^{\text {Adj }}$ deciles within each characteristic decile. Dependence ranges from low (group 1) to high (group 10) which implies that $J_{1}^{\text {Adj }}$ consists of the stocks with high downside risk and $J_{10}^{A d j}$ 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 UK stocks listed between January 1987 and May 2015. We proxy the market portfolio with the FTSE 100 index and the risk free rate with the 3 -month UK Treasury 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: $\beta / \beta^{-}$Sorted Portfolios |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\beta_{1}$ | $\beta_{2}$ | $\beta_{3}$ | $\beta_{4}$ | $\beta_{5}$ | $\beta_{6}$ | $\beta_{7}$ | $\beta_{8}$ | $\beta_{9}$ | $\beta_{10}$ | Diff | Avg |
| $\beta_{1}^{-}$ | -0.019 | 0.014 | -0.010 | -0.038 | -0.116 | -0.169 | -0.100 | -0.275 | -0.352 | -0.473 | -0.454 | -0.055 |
| $\beta_{2}^{-}$ | -0.004 | 0.041 | 0.033 | 0.022 | -0.044 | -0.058 | -0.047 | -0.088 | -0.219 | -0.387 | -0.383 | 0.001 |
| $\beta_{3}^{-}$ | -0.022 | 0.057 | 0.043 | 0.031 | 0.003 | 0.011 | 0.022 | -0.081 | -0.055 | -0.222 | -0.200 | 0.020 |
| $\beta_{4}^{-}$ | -0.055 | 0.040 | 0.038 | 0.033 | 0.025 | 0.034 | -0.007 | -0.051 | -0.082 | -0.194 | -0.139 | 0.013 |
| $\beta_{5}^{-}$ | -0.078 | 0.015 | 0.031 | 0.036 | 0.043 | 0.027 | -0.007 | -0.008 | -0.107 | -0.081 | -0.003 | 0.011 |
| $\beta_{6}^{-}$ | -0.049 | 0.028 | 0.014 | 0.022 | 0.037 | 0.026 | 0.024 | -0.014 | -0.060 | -0.115 | -0.065 | 0.007 |
| $\beta_{7}^{-}$ | -0.212 | -0.002 | -0.022 | 0.004 | 0.031 | 0.005 | 0.034 | 0.001 | -0.048 | -0.087 | 0.124 | -0.009 |
| $\beta_{8}^{-}$ | -0.287 | -0.098 | 0.009 | -0.048 | 0.025 | 0.021 | 0.025 | 0.003 | -0.032 | -0.048 | 0.239 | -0.014 |
| $\beta_{9}^{-}$ | -0.331 | -0.071 | -0.020 | -0.044 | -0.041 | -0.018 | -0.026 | -0.032 | -0.016 | -0.045 | 0.286 | -0.036 |
| $\beta_{10}^{-}$ | 0.006 | 0.018 | -0.047 | -0.060 | -0.091 | -0.035 | -0.022 | -0.052 | -0.038 | -0.132 | -0.138 | -0.102 |
| Diff | -0.025 | -0.004 | 0.038 | 0.022 | -0.024 | -0.134 | -0.079 | -0.222 | -0.314 | -0.342 |  |  |
| Avg | -0.034 | 0.031 | 0.023 | 0.014 | 0.008 | 0.005 | 0.005 | -0.027 | -0.045 | -0.121 |  |  |
| Panel B: $\beta / J^{\text {Adj }}$ Sorted Portfolios |  |  |  |  |  |  |  |  |  |  |  |  |
|  | $\beta_{1}$ | $\beta_{2}$ | $\beta_{3}$ | $\beta_{4}$ | $\beta_{5}$ | $\beta_{6}$ | $\beta_{7}$ | $\beta_{8}$ | $\beta_{9}$ | $\beta_{10}$ | Diff | Avg |
| $J_{1}^{\text {Adj }}$ | 0.109 | 0.096 | 0.071 | 0.089 | 0.098 | 0.129 | 0.169 | 0.078 | 0.100 | 0.208 | 0.099 | 0.118 |
| $J_{2}^{\text {Adj }}$ | 0.037 | 0.069 | 0.098 | 0.065 | 0.054 | 0.049 | 0.048 | 0.029 | 0.005 | 0.008 | -0.029 | 0.046 |
| $J_{3}^{\text {Adj }}$ | 0.062 | 0.113 | 0.092 | 0.055 | 0.070 | 0.046 | 0.030 | 0.013 | -0.012 | 0.012 | -0.050 | 0.047 |
| $J_{4}^{\text {Adj }}$ | 0.021 | 0.089 | 0.092 | 0.055 | 0.053 | 0.007 | 0.028 | 0.006 | 0.010 | -0.043 | -0.064 | 0.026 |
| $J_{5}^{\text {Adj }}$ | 0.018 | 0.095 | 0.050 | 0.052 | 0.031 | 0.047 | 0.048 | 0.019 | 0.015 | -0.077 | -0.096 | 0.019 |
| $J_{6}^{\text {Adj }}$ | -0.024 | 0.038 | 0.049 | 0.023 | 0.022 | 0.024 | 0.028 | 0.012 | -0.002 | -0.038 | -0.014 | 0.008 |
| $J_{7}^{\text {Adj }}$ | -0.044 | 0.014 | 0.027 | 0.044 | 0.021 | 0.027 | 0.022 | -0.013 | -0.036 | -0.083 | -0.039 | -0.011 |
| $J_{8}^{\text {Adj }}$ | -0.129 | 0.007 | -0.018 | -0.021 | 0.003 | -0.008 | 0.005 | -0.011 | -0.051 | -0.108 | 0.020 | -0.043 |
| $J_{9}^{\text {Adj }}$ | -0.098 | -0.041 | -0.040 | -0.046 | -0.047 | -0.047 | -0.045 | -0.068 | -0.074 | -0.140 | -0.042 | -0.075 |
| $J_{10}^{\text {Adj }}$ | -0.165 | -0.094 | -0.115 | -0.095 | -0.107 | -0.103 | -0.118 | -0.156 | -0.182 | -0.352 | -0.187 | -0.183 |
| Diff | 0.274 | 0.190 | 0.186 | 0.185 | 0.205 | 0.232 | 0.287 | 0.234 | 0.282 | 0.560 |  |  |
| Avg | -0.034 | 0.031 | 0.023 | 0.014 | 0.008 | 0.005 | 0.005 | -0.027 | -0.045 | -0.121 |  |  |

The Time Series Average Returns for Double Sorted Portfolios Continued
Table 2: Continued.

|  | Panel C: Size/ $J^{\text {Adj }}$ Sorted Portfolios |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $M_{1}$ | $M_{2}$ | $M_{3}$ | $M_{4}$ | $M_{5}$ | $M_{6}$ | $M_{7}$ | $M_{8}$ | $M_{9}$ | $M_{10}$ | Diff | Avg |
| $J_{1}^{\text {Adj }}$ | 0.193 | 0.145 | 0.172 | 0.126 | 0.130 | 0.087 | 0.082 | 0.046 | 0.001 | 0.126 | 0.067 | 0.118 |
| $J_{2}^{\text {Adj }}$ | 0.058 | 0.089 | 0.080 | 0.066 | 0.053 | 0.054 | 0.059 | 0.020 | -0.002 | -0.007 | 0.065 | 0.046 |
| $J_{3}^{\text {Adj }}$ | 0.042 | 0.085 | 0.092 | 0.081 | 0.078 | 0.038 | 0.052 | 0.029 | 0.005 | 0.000 | 0.042 | 0.047 |
| $J_{4}^{\text {Adj }}$ | 0.056 | 0.038 | 0.043 | 0.074 | 0.051 | 0.030 | 0.039 | -0.014 | 0.004 | -0.020 | 0.076 | 0.026 |
| $J_{5}^{\text {Adj }}$ | 0.052 | 0.031 | 0.046 | 0.052 | 0.058 | 0.043 | 0.025 | -0.020 | -0.010 | -0.030 | 0.082 | 0.019 |
| $J_{6}^{\text {Adj }}$ | 0.068 | 0.004 | 0.040 | 0.006 | 0.029 | 0.015 | 0.015 | -0.016 | -0.008 | -0.025 | 0.093 | 0.008 |
| $J_{7}^{\text {Adj }}$ | 0.064 | -0.003 | -0.035 | 0.004 | -0.008 | 0.017 | -0.005 | -0.026 | -0.031 | -0.036 | 0.100 | -0.011 |
| $J_{8}^{\text {Adj }}$ | -0.021 | -0.045 | -0.037 | -0.018 | -0.070 | -0.040 | -0.043 | -0.029 | -0.083 | -0.037 | 0.015 | -0.043 |
| $J_{9}^{\text {Adj }}$ | -0.091 | -0.083 | -0.052 | -0.076 | -0.084 | -0.089 | -0.064 | -0.067 | -0.087 | -0.066 | -0.025 | -0.075 |
| $J_{10}^{\text {Adj }}$ | -0.226 | -0.172 | -0.165 | -0.171 | -0.179 | -0.165 | -0.200 | -0.163 | -0.177 | -0.195 | -0.031 | -0.183 |
| Diff | 0.418 | 0.316 | 0.337 | 0.297 | 0.309 | 0.252 | 0.282 | 0.209 | 0.178 | 0.321 |  |  |
| Avg | 0.004 | -0.002 | 0.007 | -0.004 | -0.015 | -0.021 | -0.027 | -0.040 | -0.057 | -0.059 |  |  |
| Panel D: Coskewness/ $J^{\text {Adj }}$ Sorted Portfolios |  |  |  |  |  |  |  |  |  |  |  |  |
|  | $C_{1}$ | $C_{2}$ | $C_{3}$ | $C_{4}$ | $C_{5}$ | $C_{6}$ | $C_{7}$ | $C_{8}$ | $C_{9}$ | $C_{10}$ | Diff | Avg |
| $J_{1}^{\text {Adj }}$ | 0.054 | 0.080 | 0.105 | 0.117 | 0.169 | 0.168 | 0.104 | 0.113 | 0.228 | 0.163 | -0.109 | 0.118 |
| $J_{2}^{\text {Adj }}$ | 0.032 | 0.054 | 0.058 | 0.055 | 0.063 | 0.037 | 0.001 | 0.039 | 0.038 | 0.073 | -0.041 | 0.046 |
| $J_{3}^{\text {Adj }}$ | 0.035 | 0.045 | 0.061 | 0.061 | 0.014 | 0.053 | 0.043 | 0.013 | 0.024 | 0.115 | -0.080 | 0.047 |
| $J_{4}^{\text {Adj }}$ | 0.034 | 0.017 | 0.042 | 0.034 | 0.032 | 0.020 | -0.011 | -0.001 | 0.016 | 0.064 | -0.030 | 0.026 |
| $J_{5}^{\text {Adj }}$ | 0.032 | 0.019 | 0.011 | 0.035 | 0.012 | 0.022 | 0.017 | 0.002 | 0.021 | 0.020 | 0.012 | 0.019 |
| $J_{6}^{\text {Adj }}$ | 0.003 | 0.035 | 0.030 | 0.033 | 0.016 | -0.010 | -0.004 | -0.023 | -0.026 | 0.016 | -0.013 | 0.008 |
| $J_{7}^{\text {Adj }}$ | -0.027 | 0.019 | 0.041 | 0.029 | 0.023 | -0.011 | -0.016 | -0.040 | -0.060 | -0.038 | 0.012 | -0.011 |
| $J_{8}^{\text {Adj }}$ | -0.079 | -0.013 | -0.020 | -0.017 | -0.017 | 0.012 | -0.003 | -0.050 | -0.076 | -0.088 | 0.009 | -0.043 |
| $J_{9}^{\text {Adj }}$ | -0.101 | -0.043 | -0.052 | -0.052 | -0.044 | -0.018 | -0.052 | -0.040 | -0.111 | -0.114 | 0.013 | -0.075 |
| $J_{10}^{\text {Adj }}$ | -0.223 | -0.163 | -0.121 | -0.152 | -0.122 | -0.148 | -0.148 | -0.171 | -0.236 | -0.203 | -0.021 | -0.183 |
| Diff | 0.277 | 0.243 | 0.225 | 0.269 | 0.292 | 0.316 | 0.252 | 0.283 | 0.465 | 0.365 |  |  |
| Avg | 0.002 | 0.016 | 0.024 | 0.016 | 0.010 | -0.001 | -0.026 | -0.045 | -0.081 | -0.091 |  |  |

## Ang et al. (2006) Value-weighted Regressions (1987-2015)

Table 3: We measure risk premia using the Ang et al. (2006) asset pricing procedure where valueweighted 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 $\beta, \beta^{-}, \beta^{+}$, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and $J^{\text {Adj }}$ 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 FTSE 100 index and the risk free rate with the 3-month UK Treasury Bill rate. All regressors are Winsorised at the $1 \%$ and $99 \%$ level at each month. We restrict our attention to UK stocks listed between January 1987 and May 2015. 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 value-weighted mean and value-weighted 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 <br> (std) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Int | 0.443 | 0.030 | 0.374 | 0.376 | 0.335 |  |
|  | [3.524] | [1.549] | [3.359] | [3.361] | [2.844] |  |
| $\beta$ | -0.006 |  | -0.006 | -0.007 |  | 0.619 |
|  | [1.455] |  | [1.425] | [1.554] |  | (0.411) |
| $\beta-$ |  | -0.033 |  |  | 0.051 | 0.750 |
|  |  | [1.408] |  |  | [2.262] | (0.558) |
| $\beta+$ |  | -0.054 |  |  | -0.087 | 0.538 |
|  |  | [2.931] |  |  | [3.599] | (0.573) |
| Log-size | -0.013 |  | -0.012 | -0.012 | -0.010 | 19.974 |
|  | [2.548] |  | [2.431] | [2.422] | [1.917] | (0.771) |
| BM | -0.017 |  | -0.013 | -0.012 | -0.011 | 0.859 |
|  | [1.987] |  | [1.685] | [1.627] | [1.477] | (1.692) |
| Past ret | -0.233 |  | -0.177 | -0.177 | -0.165 | -0.002 |
|  | [1.307] |  | [1.017] | [1.017] | [0.958] | (0.037) |
| Idio | -8.919 |  | -8.221 | -8.160 | -7.871 | 0.021 |
|  | [5.116] |  | [5.028] | [5.007] | [5.196] | (0.017) |
| Cosk | -0.054 |  | 0.163 | 0.162 | 0.398 | -0.083 |
|  | [1.683] |  | [3.620] | [3.598] | [4.293] | (0.185) |
| Cokurt | -0.009 |  | 0.000 | 0.000 | 0.013 | 1.545 |
|  | [0.800] |  | [0.005] | [0.030] | [1.081] | (1.161) |
| $J^{\text {Adj }}$ |  |  | -0.011 |  |  | -2.336 |
|  |  |  | [5.182] |  |  | (7.971) |
| $J^{\text {Adj }}-$ |  |  |  | -0.011 | -0.011 | -6.201 |
|  |  |  |  | [4.812] | [4.850] | (3.766) |
| $J^{\text {Adj }}+$ |  |  |  | -0.012 | -0.012 | 6.161 |
|  |  |  |  | [4.756] | [4.695] | (4.334) |

Fama and MacBeth (1973) Regression Specifications (1987-2015) Table 4: We measure risk premia using the Fama and MacBeth (1973) asset pricing procedure where value-weighted cross-sectional regressions are computed every month rolling forward. At a given month, $t$, the average of the mean of the next $1,3,6,9,12$ and 15 months of excess monthly returns is regressed against $\beta$, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt"), $J^{\text {Adj }-~}$ and $J^{A d j}+$ 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 proxy the market portfolio with the FTSE 100 index and the risk free rate with the 3-month UK Treasury Bill rate. We restrict our attention to UK stocks listed between January 1987 and May 2015. 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 are reported as effective annual rates.

|  | 1 month |  | 3 months |  | 6 months |  | 9 months |  | 12 months |  | 15 months |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | III' | IV' | III' | IV' | III' | IV' | III' | IV' | III' | IV' | III' | IV' |
| Int | 0.150 | 0.102 | 0.160 | 0.123 | 0.192 | 0.163 | 0.201 | 0.180 | 0.209 | 0.191 | 0.218 | 0.202 |
|  | [1.222] | [0.817] | [1.202] | [0.920] | [1.489] | [1.270] | [1.625] | [1.459] | [1.817] | [1.664] | [2.044] | [1.912] |
| $\beta$ | -0.095 | -0.105 | -0.087 | -0.096 | -0.089 | -0.096 | -0.086 | -0.092 | -0.079 | -0.083 | -0.070 | -0.074 |
|  | [2.443] | [2.652] | [2.345] | [2.548] | [2.486] | [2.639] | [2.540] | [2.661] | [2.620] | [2.731] | [2.627] | [2.746] |
| Log-size | -0.005 | -0.004 | -0.008 | -0.007 | -0.010 | -0.009 | -0.011 | -0.010 | -0.011 | -0.011 | -0.012 | -0.011 |
|  | [0.945] | [0.763] | [1.252] | [1.163] | [1.611] | [1.535] | [1.758] | [1.690] | [1.934] | [1.877] | [2.165] | [2.121] |
| BM | 0.013 | 0.013 | 0.018 | 0.019 | 0.019 | 0.019 | 0.017 | 0.017 | 0.014 | 0.014 | 0.012 | 0.012 |
|  | [1.769] | [1.826] | [2.211] | [2.250] | [2.248] | [2.255] | [2.122] | [2.093] | [1.926] | [1.918] | [1.672] | [1.664] |
| Past ret | 0.285 | 0.292 | 0.479 | 0.488 | 0.257 | 0.274 | 0.027 | 0.035 | -0.123 | -0.119 | -0.159 | -0.157 |
|  | [0.781] | [0.797] | [1.405] | [1.417] | [0.854] | [0.902] | [0.100] | [0.129] | [0.510] | [0.491] | [0.739] | [0.724] |
| Idio | -3.384 | -3.327 | -2.127 | -2.047 | -1.227 | -1.169 | -0.800 | -0.768 | -0.582 | -0.550 | -0.450 | -0.427 |
|  | [4.600] | [4.590] | [3.435] | [3.400] | [2.264] | [2.194] | [1.563] | [1.498] | [1.233] | [1.162] | [1.059] | [0.993] |
| Cosk | 0.288 | 0.296 | 0.110 | 0.114 | 0.075 | 0.078 | 0.046 | 0.049 | 0.043 | 0.045 | 0.036 | 0.038 |
|  | [3.233] | [3.279] | [2.281] | [2.325] | [1.905] | [1.949] | [1.452] | [1.530] | [1.637] | [1.692] | [1.463] | [1.503] |
| Cokurt | 0.041 | 0.047 | 0.029 | 0.034 | 0.025 | 0.029 | 0.021 | 0.024 | 0.019 | 0.022 | 0.018 | 0.020 |
|  | [2.701] | [2.931] | [2.546] | [2.820] | [2.208] | [2.427] | [1.955] | [2.105] | [1.911] | [2.031] | [2.066] | [2.185] |
| $J^{\text {Adj }}$ | -0.010 |  | -0.004 |  | -0.003 |  | -0.002 |  | -0.001 |  | -0.001 |  |
|  | [6.429] |  | [4.856] |  | [3.480] |  | [2.982] |  | [2.625] |  | [2.164] |  |
| $J^{\text {Adj }}-$ |  | -0.014 |  | -0.008 |  | -0.005 |  |  |  |  |  |  |
|  |  | [6.028] |  | [4.770] |  | [3.918] |  | [3.559] |  | [3.388] |  | [3.294] |
| $J^{\text {Adj }}+$ |  | -0.0062 |  | -0.0006 |  | 0.0005 |  | 0.0004 |  | 0.0006 |  | 0.0007 |
|  |  | [3.853] |  | [0.446] |  | [0.428] |  | [0.366] |  | [0.604] |  | [0.737] |



Figure 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.


Figure 2: Actual and hypothetical distribution under multivariate normality of the $J^{A d j}$. Plot (a) depicts the actual distribution is estimated on ASX stocks listed between June 1992 and May 2015. We proxy the market portfolio with the FTSE 100 index and the risk free rate with the 3-month UK Treasury Bill rate. In plot (b), we present the simulated distribution of $J^{\text {Adj }}$ based on multivariate normal data.


Figure 3: This figure depicts the median factor loading for $\beta, J^{A d j}-$ and $J^{A d j}+$ at a given month, $t$, between January 2000 and May 2015 using the past 12 months of daily excess returns. We proxy the market portfolio with the FTSE 100 index and the risk free rate with the 3-month UK Treasury Bill rate. The estimate is calculated using all historical data up to and including time $t$.


Figure 4: This figure depicts the factor sensitivity using the Ang et al. (2006) 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 $\beta$, idiosyncratic risk, coskewness, cokurtosis, $J^{A d j}-$ and $J^{A d j}+$ 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 FTSE 100 index and the risk free rate with the 3 -month UK Treasury Bill rate. All regressors are Winsorised at the $1 \%$ and $99 \%$ level at each month. We restrict our attention to UK stocks listed between January 1987 and May 2015. The Premium for $\beta$ and for $J^{A d j}$ - and the Discount for $J^{A d j}+$ between January 2000 and May 2015 is given by the time series median factor sensitivity using all historical sensitivity estimates up to and including time $t$.

## Appendix: Robustness Tests

## Ang et al. (2006) Equally-weighted Regressions (1987-2015)

Table 5: We measure risk premia using the Ang et al. (2006) asset pricing procedure where equally-weighted 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 $\beta, \beta^{-}$, $\beta^{+}$, 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 FTSE 100 index and the risk free rate with the 3 -month UK Treasury Bill rate. All regressors are Winsorised at the $1 \%$ and $99 \%$ level at each month. We restrict our attention to UK stocks listed between January 1987 and May 2015. 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 equally-weighted mean and equally-weighted 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 <br> (std) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Int | 0.418 | 0.031 | 0.344 | 0.343 | 0.353 |  |
|  | [2.909] | [1.532] | [2.687] | [2.636] | [2.918] |  |
| $\beta$ | -0.041 |  | -0.049 | -0.050 |  | 0.605 |
|  | [1.064] |  | [1.293] | [1.299] |  | (0.409) |
| $\beta-$ |  | -0.034 |  |  | 0.051 | 0.740 |
|  |  | [1.421] |  |  | [2.312] | (0.518) |
| $\beta+$ |  | -0.053 |  |  | -0.084 | 0.521 |
|  |  | [2.897] |  |  | [3.566] | (0.531) |
| Log-size | -0.012 |  | -0.010 | -0.010 | -0.011 | 19.835 |
|  | [1.915] |  | [1.751] | [1.734] | [2.029] | (0.794) |
| BM | -0.018 |  | -0.014 | -0.014 | -0.012 | 0.883 |
|  | [2.168] |  | [1.895] | [1.835] | [1.565] | (1.660) |
| Past ret | -0.323 |  | -0.267 | -0.266 | -0.195 | -0.002 |
|  | [1.705] |  | [1.453] | [1.445] | [1.123] | (0.038) |
| Idio | -8.438 |  | -7.672 | -7.583 | -7.900 | 0.021 |
|  | [5.292] |  | [5.234] | [5.220] | [5.211] | (0.018) |
| Cosk | -0.042 |  | 0.175 | 0.173 | 0.398 | -0.085 |
|  | [1.357] |  | [3.931] | [3.889] | [4.327] | (0.185) |
| Cokurt | -0.004 |  | 0.008 | 0.008 | 0.012 | 1.517 |
|  | [0.450] |  | [0.864] | [0.845] | [1.055] | (1.157) |
| $J^{A d j}$ |  |  | -0.011 |  |  | -2.386 |
|  |  |  | [5.167] |  |  | (6.973) |
| $J^{\text {Adj }}-$ |  |  |  | -0.011 | -0.011 | -6.235 |
|  |  |  |  | [5.006] | [4.866] | (3.778) |
| $J^{\text {Adj }}+$ |  |  |  | -0.012 | -0.012 | 6.175 |
|  |  |  |  | [4.547] | [4.702] | (4.332) |

Fama and MacBeth (1973) Regression Specifications (1987-2015)
Table 6. We measure risk prese (1973) asset pricing procedure where value-weighted cross-sectional regressions are computed every month rolling forward. At a given month, $t$, the average of the next excess monthly return is regressed against $\beta$, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt"), $J^{A d j}$ - and $J^{A d j}+$ 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 returns. We proxy the market portfolio with the FTSE 100 index and the risk free rate with the 3-month UK Treasury Bill rate. We restrict our attention to UK stocks listed between January 1987 and May 2015. 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 value-weighted mean and value-weighted standard deviation (in parentheses) for each variable is provided. All coefficients are reported as effective annual rates.

|  | All |  |  | Excl Top Quintile |  |  | Excl Top Decile |  |  | Excl Top Vigintile |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | I' | IV' | Mean (Std) | I' | IV' | Mean (Std) | I' | IV' | Mean (Std) | I' | IV' | Mean <br> (Std) |
| Int | 0.216 | 0.102 |  | 0.234 | 0.121 |  | 0.234 | 0.120 |  | 0.235 | 0.121 |  |
|  | [1.727] | [0.817] |  | [1.849] | [0.957] |  | [1.858] | [0.955] |  | [1.867] | [0.966] |  |
| $\beta$ | -0.089 | -0.105 | 0.620 | -0.084 | -0.102 | 0.616 | -0.085 | -0.102 | 0.616 | -0.085 | -0.102 | 0.616 |
|  | [2.333] | [2.652] | (0.411) | [2.213] | [2.559] | (0.405) | [2.227] | [2.572] | (0.405) | [2.223] | [2.568] | (0.405) |
| Log-size | -0.007 | -0.004 | 19.976 | -0.008 | -0.005 | 19.984 | -0.008 | -0.005 | 19.984 | -0.008 | -0.005 | 19.984 |
|  | [1.236] | [0.763] | (0.769) | [1.382] | [0.928] | (0.746) | [1.389] | [0.926] | (0.746) | [1.399] | [0.936] | (0.746) |
| BM | 0.010 | 0.013 | 0.859 | 0.011 | 0.014 | 0.851 | 0.011 | 0.014 | 0.851 | 0.011 | 0.014 | 0.851 |
|  | [1.450] | [1.826] | (1.691) | [1.586] | [1.965] | (1.680) | [1.575] | [1.956] | (1.681) | [1.566] | [1.947] | (1.681) |
| Past ret | 0.715 | 0.292 | -0.002 | 0.674 | 0.226 | -0.002 | 0.679 | 0.232 | -0.002 | 0.677 | 0.229 | -0.002 |
|  | [1.942] | [0.797] | (0.037) | [1.787] | [0.604] | (0.036) | [1.804] | [0.620] | (0.036) | [1.799] | [0.613] | (0.036) |
| Idio | -3.871 | -3.327 | 0.021 | -3.946 | -3.395 | 0.021 | -3.942 | -3.389 | 0.021 | -3.946 | -3.397 | 0.021 |
|  | [4.948] | [4.590] | (0.017) | [4.945] | [4.576] | (0.017) | [4.946] | [4.577] | (0.017) | [4.951] | [4.586] | (0.017) |
| Cosk | 0.085 | 0.296 | -0.085 | 0.074 | 0.287 | -0.085 | 0.076 | 0.288 | -0.085 | 0.076 | 0.287 | -0.085 |
|  | [1.088] | [3.279] | (0.185) | [0.954] | [3.195] | (0.186) | [0.977] | [3.197] | (0.186) | [0.970] | [3.192] | (0.186) |
| Cokurt | 0.030 | 0.047 | 1.520 | 0.028 | 0.046 | 1.520 | 0.028 | 0.046 | 1.520 | 0.028 | 0.046 | 1.520 |
|  | [2.158] | [2.931] | (1.162) | [2.109] | [2.937] | (1.167) | [2.127] | [2.951] | (1.167) | [2.130] | [2.952] | (1.167) |
| $J^{\text {Adj }}-$ |  | -0.014 | -6.234 |  | -0.015 | -6.234 |  | -0.014 | -6.234 |  | -0.014 | -6.234 |
|  |  | [6.028] | (3.766) |  | [6.018] | (3.752) |  | [6.015] | (3.752) |  | [6.015] | (3.751) |
| $J^{\text {Adj }}+$ |  | -0.0062 | 6.165 |  | -0.0061 | 6.165 |  | -0.0061 | 6.165 |  | -0.0061 | 6.165 |
|  |  | [3.853] | (4.325) |  | [3.803] | (4.351) |  | [3.763] | (4.350) |  | [3.778] | (4.348) |

## Ang et al. (2006) Value-weighted Regressions (1988-2014)

Table 7: We measure risk premia using the Ang et al. (2006) asset pricing procedure where valueweighted 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 $\beta, \beta^{-}, \beta^{+}$, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and $J^{\text {Adj }}$ 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 FTSE 100 index and the risk free rate with the 3 -month UK Treasury Bill rate. All regressors are Winsorised at the $1 \%$ and $99 \%$ level at each month. We restrict our attention to UK stocks listed between January 1988 and May 2015. 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 value-weighted mean and value-weighted 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 <br> (std) |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Int | 0.419 | 0.029 | 0.350 | 0.350 | 0.366 |  |
| $\beta$ | $[2.939]$ | $[1.481]$ | $[2.753]$ | $[2.721]$ | $[3.080]$ |  |
|  | -0.038 |  | -0.045 | -0.045 |  | 0.604 |
| $\beta-$ | $[0.991]$ |  | $[1.209]$ | $[1.199]$ |  | $(0.408)$ |
|  |  | -0.038 |  |  | 0.046 | 0.739 |
| $\beta+$ |  | $[1.616]$ |  |  | $[2.100]$ | $(0.518)$ |
|  |  | -0.049 |  | -0.081 | 0.520 |  |
| Log-size | -0.013 | $[2.767]$ |  |  | $[3.481]$ | $(0.531)$ |
|  | $[2.017]$ |  | -0.011 | -0.011 | -0.011 | 19.831 |
| BM | -0.019 |  | $[1.883]$ | $[1.861]$ | $[2.190]$ | $(0.795)$ |
|  | $[2.288]$ |  | -0.015 | -0.015 | -0.013 | 0.883 |
| Past ret | -0.267 |  | -0.213 | $[1.937]$ | $[1.817]$ | $(1.660)$ |
|  | $[1.460]$ |  | -0.210 | -0.147 | -0.002 |  |
| Idio | -8.010 |  | -7.276 | $[1.186]$ | $[0.875]$ | $(0.038)$ |
|  | $[5.137]$ |  | $[5.081]$ | $[5.221$ | -7.544 | 0.021 |
| Cosk | -0.037 |  | 0.174 | 0.172 | $[5.058]$ | $(0.018)$ |
|  | $[1.200]$ |  | $[3.911]$ | $[3.880]$ | $[4.187]$ | $(0.185)$ |
| Cokurt | -0.005 |  | 0.006 | 0.006 | 0.011 | 1.516 |
|  | $[0.512]$ |  | $[0.713]$ | $[0.642]$ | $[0.943]$ | $(1.159)$ |
| $J^{\text {Adj }}$ |  | -0.011 |  |  | -2.385 |  |
|  |  |  |  |  |  | $-0.079]$ |
| $J^{\text {Adj }}-$ |  |  |  | $[4.878]$ | $[4.722]$ | $(3.775)$ |
| $J^{\text {Adj }}+$ |  |  |  | -0.012 | -0.012 | 6.173 |
|  |  |  |  |  |  |  |


[^0]:    * Corresponding Author: Petra Andrlikova, The University of Sydney, Sydney, Australia 2006. Email: andrlikova@gmail.com.

[^1]:    ${ }^{2}$ The set of preferences ( $u, \beta$ ) satisfying (1), are risk averse if and only if $\beta \geq 0$ and $u$ is concave (see Gul (1991), Theorem 3 for proof). Furthermore, $\left(u_{1}, \beta_{1}\right)$ is more risk averse than $\left(u_{2}, \beta_{2}\right)$ if $\beta_{1} \geq \beta_{2}$ and $R_{u_{1}}^{a}(x) \geq R_{u_{2}}^{a}(x)$ for all $x$, where $R_{u}^{a}(x)=-u^{\prime \prime}(x) / u^{\prime}(x)$, the coefficient of absolute risk aversion (see Gul (1991), Theorem 5 for proof). It follows that if $\left(u_{1}, \beta_{1}\right)$ is more risk averse than $\left(u_{2}, \beta_{2}\right)$, then $\beta_{1} \geq \beta_{2}$. Although Gul (1991) preferences improve upon traditional utility preferences in the explanation of asset return dynamics, they fail to sufficiently account for observed risk premium variability (Bekaert et al., 1997) and cannot accommodate

[^2]:    ${ }^{3}$ Note that the lower the value of $J^{\text {Adj }}$, the higher the level of AD for firms with LTAD $(66 \%$ in the sample).

[^3]:    ${ }^{4}$ Harvey et al. (2014) suggest that a higher hurdle rate of 3.0 for the $t$-statistic should be used in explaining the cross section of expected returns to control for data mining, correlation among the tests and missing data.

