Asymmetric Dependence in Finance
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Asymmetric Dependence in Finance

Diversification, Correlation and Portfolio Management in Market Downturns

EDITED BY
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WILEY
To the memory of John Knight
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Dr Satchell was an Academic Advisor to JP Morgan Asset Management, the Governor of the Bank of Greece and for a year in the Prime Minister’s department in London.
Introduction

Symmetric dependence (hereafter, AD) is usually thought of as a cross-sectional phenomenon. Andrew Patton describes AD as ‘stock returns appear to be more highly correlated during market downturns than during market upturns’ (Patton, 2004).\(^1\) Thus, at a point in time when the market return is increasing, we might expect to find the correlation between any two stocks to be, on average, lower than the correlation between those same two stocks when the market return is negative. However, the term can also have a time-series interpretation. Thus, it may be that the impact of the current US market on the future UK market may be quantitatively different from the impact of the current UK market on the future US market. This is also a notion of AD that occurs through time. Whilst most of this book addresses the former notion of AD, time-series AD is explored in Chapters 4 and 7.

Readers may think that discussion of AD commenced during the Global Financial Crisis (GFC) of 2007–2009, however scholars have been exploring this topic in finance since the early 1990s. Mathematical statisticians have investigated asymmetric asymptotic tail dependence for much longer. The evidence thus far has found that the cross-sectional correlation between stock returns has generally been much higher during downturns than during upturns. This phenomenon has been observed at the stock and the index level, both within countries and across countries. Whilst less analysis of time-series AD with relation to market states has been carried out, it is highly likely that the results for time-series AD will depend upon the frequency of data observation and the conditioning information set, *inter alia*.

The ideas behind the measurement of AD depend upon computing correlations over subsets of the range of possible values that returns can take. Assuming that the original data comes from a constant correlation distribution, once we truncate the range of values, the conditional correlation will change. This is the idea behind one of the key tools of analysis, the exceedance correlation. To understand the power of this technique, readers should consult Panels A and B on p. 454 of Ang and Chen (2002).\(^2\) The distributional assumptions for the data generating process now become critical. It can be shown that, as we move further into the tails, the exceedance correlation for a multivariate normal distribution tends to zero. Intuitively, this means that multivariate normally distributed random variables approach independence in the tails. Empirical plots in the analysis of AD tend to suggest that, in the lower tail at least, the near independence phenomenon does not occur. Thus we are led to consider other distributions than normality, an approach addressed throughout this book.

The most obvious impact of AD in financial returns is its effect on risk diversification. To understand this, we look at quantitative fund managers whose behaviour is described as follows. They typically use mean-variance analysis to model the trade-off between return and risk. The risk (variance) of a portfolio will depend upon the variances and correlations of the stocks in the portfolio. Optimal investments are chosen based on these numbers. One feature of such mean-variance strategies


is that one often ends up investing in a small number of funds and all other risks are diversified away as idiosyncratic correlations will average out. However, if these correlations tend to one then the averaging process will not eliminate idiosyncratic risks, diversification fails and the optimal positions chosen are no longer optimal. Said another way, risk will be underestimated and hedging strategies will no longer be effective.

The example above is just one case where AD will affect financial decision making. To the extent that AD influences the optimal portfolios of investors, it will clearly also affect the allocation of capital within the broader market and hence the cost of that capital to corporate entities. An understanding of AD as a financial phenomenon is not only important to financial risk managers but also to other senior executives in organizations. Solutions for managing AD are scarce, however Chapter 5 provides some answers to these problems.

This book looks at explanations for the ubiquitous nature of AD. One explanation that is attractive to economists is that AD derives from the preferences (utility functions) of individual market agents. Whilst quadratic preferences typically lead to relatively symmetric behaviour, theories such as loss aversion or disappointment aversion give expected utilities that have built-in asymmetries with respect to future wealth. These preferences and their implications are discussed in Chapter 1. Such structures lead to the pricing of AD, and coupled with suitable dynamic processes for prices will generate AD that, theoretically at least, could be observed in financial markets. Chapter 3 explores the pricing of AD within the US equities market. These chapters discuss non-linearity in utility as a potential source of AD. Another approach that will give similar outcomes is to model the dynamic price processes in non-linear terms. Such an approach is carried out in Chapters 2 and 4.

It is understood that the origins of AD may well have a basis in individual and collective utility. This idea is investigated in Chapter 1, where Jamie Alcock and Anthony Hatherley explore the AD preferences of disappointment-averse investors and how these preferences filter into asset pricing. One of the advantages of the utility approach is that it can be used to define gain and loss measures. The authors develop a new metric to capture AD based upon disappointment aversion and they show how it is able to capture AD in an economic and statistically meaningful manner. They also show that this measure is better able to capture AD than commonly used competing methods. The theory developed in this chapter is subsequently utilized in various ways in Chapters 3 and 9.

One explanation of AD is based on notions of non-linear random variables. Stephen Satchell and Oliver Williams use this framework in Chapter 2 to build a model of a market where an option and a share are both traded, and investors combine these instruments into portfolios. This will lead to AD on future prices. The innovation in this chapter is to use mean-variance preferences that add a certain amount of tractability. This model is then used to assess the factors that determine the size of the commodity trading advisor (CTA) market. This question is of some importance, as CTA returns seem to have declined as the volume of funds invested in them has increased. The above provides another explanation of the occurrence of AD.

In Chapter 3, Jamie Alcock and Anthony Hatherley investigate the pricing of AD. Using a metric developed in Chapter 1, they demonstrate that AD is significantly priced in the market and has a market price approximately 50% of the market price of $\beta$ risk. In particular, lower-tail dependence has displayed a mostly constant price of 26% of the market risk premium throughout 1989–2015. In contrast, the discount associated with upper-tail dependence has nearly tripled in this time. This changed, however, during the GFC of 2007–2009. These changes through time suggest that both systematic risk and AD should be managed in order to reduce the return impact of market downturns. These findings have substantial implications for the cost of capital, investor expectations, portfolio management and performance assessment.

Chapter 4, by Salman Ahmed, Nandini Srivastava, John Knight and Stephen Satchell, addresses the role of volatility and AD therein and its implications for volatility forecasting. The authors use a novel methodology to deal with the issue that volatility cannot be observed at discrete frequencies. They review the literature and find the most convincing model that they assume to be the true model; this is an EGARCH(1,2) model. They then generate data from this true model to assess which of two commonly
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used models give better forecasts; a GARCH or stochastic volatility (SV) model. Interestingly, because the SV model captures AD whilst a GARCH model does not, it seems better able to forecast in most instances.

Whilst previous chapters have not directly addressed the question of how a risk manager could manage AD, Chapter 5 by Anthony Hatherley does precisely this. He demonstrates how an investor can hedge upper-tail dependence and lower-tail dependence risk by buying and selling multi-underlying derivatives that are sensitive to implied correlation skew. He also proposes a long–short equity derivative strategy involving corridor variance swaps that provides exposure to aggregate implied AD that is consistent with the adjusted $J$-statistic proposed in Chapter 1. This strategy provides a more direct hedge against the drivers of AD, in contrast to the current practice of simply hedging the effects of AD with volatility derivatives.

In Chapter 6, Mark Lundin and Stephen Satchell use orthant probability-based correlation as a portfolio construction technique. The ideas involved here have a direct link to AD because measures used in this chapter based on orthant probabilities can be thought of as correlations, as discussed earlier. The authors derive some new test results relevant to these problems, which may have wider applications. A $t$-value for orthant correlations is derived so that a $t$-test can be conducted and $p$-values inferred from Student’s $t$-distribution. Orthant conditional correlations in the presence of imposed skewness and kurtosis and fixed linear correlations are shown. They conclude with a demonstration that this dependence measure also carries potentially profitable return information.

From our earlier empirical discussion, we know that multivariate normality is not a distributional assumption that leads to the known empirical results of AD. Chapter 7, by Sharon Lee and Geoffrey McLachlan, assumes different distributions to model AD more in line with empirical findings. They consider the application of multivariate non-normal mixture models for modelling the joint distribution of the log returns in a portfolio. Formulas are then derived for some commonly used risk measures, including probability of shortfall (PS), Value-at-Risk (VaR), expected shortfall (ES) and tail-conditional expectation (TCE), based on these models. Their focus is on skew normal and skew $t$-component distributions. These families of distributions are generalizations of the normal distribution and $t$-distribution, respectively, with additional parameters to accommodate skewness and/or heavy tails, rendering them suitable for handling the asymmetric distributional shape of financial data. This approach is demonstrated on a real example of a portfolio of Australian stock returns and the performances of these models are compared to the traditional normal mixture model.

Following on from Chapter 7, multivariate normality cannot be justified by empirical considerations. It does have the advantage that the first two moments define all the higher moments thereby controlling, to some extent, the dimensionality of the problem. By contrast, the uncontrolled use of extra parameters rapidly leads to dimensionality issues. Artem Prokhorov, Stanislav Anatolyev and Renat Khabibullin address this issue in Chapter 8 using a sequential procedure where the joint patterns of asymmetry and dependence are unrestricted, yet the method does not suffer from the curse of dimensionality encountered in non-parametric estimation. They construct a flexible multivariate distribution using tightly parameterized lower-dimensional distributions coupled by a bivariate copula. This effectively replaces a high-dimensional parameter space with many simple estimations of few parameters. They provide theoretical motivation for this estimator as a pseudo-MLE with known asymptotic properties. In an asymmetric GARCH-type application with regional stock indices, the procedure provides an excellent fit when dimensionality is moderate. When dimensionality is high, this procedure remains operational when the conventional method fails.

Previous chapters have discussed the importance of AD in risk management but little has been said about whether AD can be forecasted. In Chapter 9, Jamie Alcock and Petra Andrlikova investigate the question of whether AD characteristics of stock returns are persistent or forecastable and whether AD could be used to forecast future returns. The authors examine the differences between the upper-tail and lower-tail AD and analyse both characteristics independently. Methods involved use ARIMA models to try to understand the patterns and cyclical behaviour of the autocorrelations with a possible extension to the family of GARCH models. They also use out-of-sample empirical asset pricing techniques to
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explore the AD predictability of stock returns. Broadly, they find that AD does not predict future AD but does predict future returns.

As previous chapters have demonstrated, copulas are a valuable tool in capturing AD, which in turn can be used to construct portfolios. Ba Chu and Stephen Satchell apply these ideas in Chapter 10 by using a copula they call the most entropic canonical copula (MECC). In an empirical study, they focus on an application of the MECC theory to a ‘style investing’ problem for an investor with a constant relative risk aversion (CRRA) utility function allocating wealth between the Russell 1000 ‘growth’ and ‘value’ indices. They use the MECC to model the dependence between the indices’ returns for their investment strategies. They find the gains from using the MECC are economically and statistically significant, in cases either with or without short-sales constraints.

In the context of managing downside correlations, Jamie Alcock, Timothy Brailsford, Robert Faff and Rand Low examine in Chapter 11 the use of multi-dimensional elliptical and asymmetric copula models to forecast returns for portfolios with 3–12 constituents. They consider the efficient frontiers produced by each model and focus on comparing two methods for incorporating scalable AD structures across asset returns using the Archimedean Clayton copula in an out-of-sample, long-run multi-period setting. For portfolios of higher dimensions, modelling asymmetries within the marginals and the dependence structure with the Clayton canonical vine copula (CVC) consistently produces the highest-ranked outcomes across a range of statistical and economic metrics when compared to other models incorporating elliptical or symmetric dependence structures. Accordingly, the authors conclude that CVC copulas are ‘worth it’ when managing larger portfolios.

Whilst we have addressed many issues relating to AD, there are too many to comprehensively address in one book. As an example of a topic that is not covered in this book, one might consider the relationship between AD and the time horizon of investment returns. A number of authors have argued that returns over very short horizons should have diffusion-like characteristics and therefore behave like Brownian motion, and hence be normally distributed. Other investigators have invoked time-series central limit theorems to argue that long-horizon returns, being the sum of many short-horizon returns, should approach normality. Since the absence of normality seems a likely requirement for AD, it may well be that AD only occurs over some investment horizons and not others.
CHAPTER 1

Disappointment Aversion, Asset Pricing and Measuring Asymmetric Dependence

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Abstract
We develop a measure of asymmetric dependence (AD) that is consistent with investors who are averse to disappointment in the utility framework proposed by Skiadas (1997). Using a Skiadas-consistent utility function, we show that disappointment aversion implies that asymmetric joint return distributions impact investor utility. From an asset pricing perspective, we demonstrate that the consequence of these preferences for the realization of a given state results in a pricing kernel adjustment reflecting the degree to which these preferences represent a departure from expected utility behaviour. Consequently, we argue that capturing economically meaningful AD requires a metric that captures the relative differences in the shape of the dependence in the upper and lower tail. Such a metric is better able to capture AD than commonly used competing methods.

1.1 INTRODUCTION

The economic significance of measuring asymmetric dependence (AD), and its associated risk premium, can be motivated by considering a utility-based framework for AD. An incremental AD risk premium is consistent with a marginal investor who derives (dis-)utility from non-diversifiable, asymmetric characteristics of the joint return distribution. The effect of these characteristics on investor utility is captured by the framework developed by Skiadas (1997). In this model, agents rank the preferences of an act in a given state depending on the state itself (state-dependence) as well as the payoffs in other states (non-separability). The agent perceives potentially subjective consequences, such as disappointment and elation, when choosing an act, \( b \in B = \{ \ldots , b, c, \ldots \} \), in the event that \( E \in \Omega = \{ \ldots , E, F, \ldots \} \) is observed,\(^1\) where \( B \) represents the set of acts that may be chosen on the set of states, \( S = \{ \ldots , s, \ldots \} \), and \( \Omega \) represents all possible resolutions of uncertainty and corresponds to the set of events that defines a \( \sigma \)-field on the universal event \( S \).

\(^1\)For example, the event \( E \) might represent a major market drawdown.
Within this context, (weak) disappointment is defined as:

\[ (b = c \text{ on } E \text{ and } c \succeq \Omega = b) \implies b \succeq Ec, \]

where the statement ‘\(b \succeq Ec\)’ has the interpretation that, ex ante, the agent regards the consequences of act \(b\) on event \(E\) as no less desirable than the consequences of act \(c\) on the same event (Skiadas, 1997, p. 350). That is, if acts \(b\) and \(c\) have the same payoff on \(E\), and the consequences of act \(b\) are generally no more desirable than the consequences of act \(c\), then the consequence of having chosen \(b\) conditional on \(E\) occurring is considered to be no less desirable than having chosen \(c\) when the agent associates a feeling of elation with \(b\) and disappointment with \(c\) conditional upon the occurrence of \(E\).

For example, consider two stocks, \(X\) and \(Y\), that have identical \(\beta\)s, equal average returns and the same level of dependence in the lower tail. Further, suppose \(Y\) displays dependence in the upper tail that is equal in absolute magnitude to the level of dependence in the lower tail, but \(X\) has no dependence in the upper tail. In this example, \(Y\) is symmetric (but not necessarily elliptical), whereas \(X\) is asymmetric, displaying lower-tail asymmetric dependence (LTAD). Within the context of the Capital Asset Pricing Model (CAPM), the expected return associated with an exposure to systematic risk should be the same for \(X\) and \(Y\) because they have the same \(\beta\). However, in addition to this, a rational, non-satiable investor who accounts for relative differences in upside and downside risk should prefer \(Y\) over \(X\) because, conditional on a market downturn event, \(Y\) is less likely to suffer losses compared with \(X\). Similarly, a downside-risk-averse investor will also prefer \(Y\) over \(X\). These preferences should imply higher returns for assets that display LTAD and lower returns for assets that display upper-tail asymmetric dependence (UTAD), independent of the returns demanded for \(\beta\).

Now, let the event \(E\) represent a major market drawdown and assume that AD is not priced by the market. In the general framework of Skiadas, an investor may prefer \(Y\) over \(X\) because \(Y\) is more likely to recover the initial loss associated with the market drawdown in the event that the market subsequently recovers. Disappointment aversion manifests itself in an additional source of ex-ante risk premium over and above the premium associated with ordinary beta risk because an investor will display greater disappointment having not invested in a stock with compensating characteristics given the drawdown event (that is, holding \(X\) instead of \(Y\)).

With regard to preferences in the event that \(E\) occurs, a disappointment-averse investor will prefer \(Y\) over \(X\) because the relative level of lower-tail dependence to upper-tail dependence is greater in \(X\) than in \(Y\). More generally, this investor prefers an asset displaying joint normality with the market.
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compared with either $X$ or $Y$ as the risk-adjusted loss given event $E$ is lower. A risk premium is required to entice a disappointment-averse investor to invest in either $X$ or $Y$, and this premium will be greater for $X$ than for $Y$.

Ang et al. (2006) employ a similar rationale based upon Gul’s (1991) disappointment-averse utility framework to decompose the standard CRRA utility function into upside and downside utility, which is then proxied by upside and downside $\beta$s. In contrast to a Skiadis agent that is endowed with a family of conditional preference relations (one for each event), Gul agents are assumed to be characterized by a single unconditional (Savage) preference relation (Grant et al., 2001). A Skiadis-consistent AD metric conditions on multiple market states, rather than a single condition such as that implied by downside or upside $\beta$.

The impact of AD on the utility of an investor who is disappointment-averse in the Skiadis sense is identified using the disappointment-averse utility function proposed by Grant, Kajii and Polak (GKP).

Define an outcome $x \in \mathcal{X} = \{ \ldots, x, y, z, \ldots \}$ such that $b(s) = x$, that is, an act $b$ on state $s$ results in outcome $x$. A disappointment-averse utility function that is consistent with Skiadis preferences is given by

$$V_{\alpha, \beta}^E(b) = \int_{s \in E} v_{\alpha, \beta}(b(s), V_{\beta}(b))d\mu,$$

(1.1)

with

$$v_{\alpha, \beta}(x, w) = \alpha \varphi(x, w) + (1 - \alpha)w$$

and

$$\varphi_{\beta}(x, w) = (x - w)(1 + \mathbb{1}_{x < \beta})$$.

(1.2)

where $\beta > -1$ is a disappointment-aversion parameter and $\mathbb{1}$ is an indicator function taking value 1 if the condition in the subscript is true, zero otherwise. The GKP utility function is consistent with Skiadis disappointment$^4$ if $\beta > \frac{1}{\alpha} - 2 > 0$. The variable $V_{\beta}(b)$ solves

$$\int_S \varphi_{\beta}(b(s), V_{\beta})d\mu = 0,$$

(1.3)

and can be interpreted as a certainty-equivalent outcome for act $b$, representing the unconditional preference relation $\succeq_{\beta}$ over the universal event $S$. Therefore, for all states $s$ in event $E$, an agent assigns utility for outcomes $b(s) = x \geq V_{\beta}$ and conversely assigns dis-utility to disappointing outcomes $b(s) = x < V_{\beta}$, where the dis-utility is scaled by $1 + \beta$. The preference, $V_{\alpha, \beta}^E(b)$, is then given by a weighted sum of the utility associated with event $E$, given by the disappointment-averse utility function, $\varphi_{\beta}(x, w)$, and the utility associated with the universal event $S$, given by the certainty equivalent, $w$.

The influence of AD on the utility of disappointment-averse investors can be explored using a simulation study. We repeatedly estimate Equation (1.1) using simulated LTAD data and multivariate normal data, where both data sets are mean-variance equivalent by construction. We simulate LTAD using a Clayton copula with a copula parameter of 1, where the asset marginals are assumed to be standard normal. A corresponding symmetric, multivariate normal distribution (MVN) is generated using the same underlying random numbers used to generate the AD data, in conjunction with the sample covariance matrix produced by the Clayton copula data. In this way, we ensure the mean-variance equivalence of the two simulated samples. The mean and variance–covariance matrices of the simulated samples have

$^4$Equation (1.1) is also consistent with Gul’s representation of disappointment aversion if $\beta > 0$. If, in addition, $\alpha > 1/(2 + \beta)$, then the conditional preference relation is consistent with Skiadis disappointment (Grant et al., 2001).
the following $L^1$- and $L^2$-norms: $||\mu_{AD} - \mu_{MVN}||_1 < 0.0001$ and $||\Sigma_{AD} - \Sigma_{MVN}||_2 < 0.01$. The certainty equivalent is generated using 50,000 realizations of the Clayton sample and the corresponding MVN sample for a given set of utility parameters, $(\alpha, \beta)$. Given the certainty-equivalent values, we estimate Equation (1.1) 20,000 times, where the realizations of the outcome, $x$, are re-sampled with each iteration using a sample size of 5,000. The certainty equivalent is computed using market realizations in conjunction with Equation (1.3).

**FIGURE 1.1** Simulated densities of GKP utility functions calculated when returns are symmetrically distributed (MVN) and asymmetrically distributed. Non-disappointment-averse utility is described by the GKP utility function (1.1) with $\alpha = 0.5$ and $\beta = 0$. Skiadas disappointment-averse utility is described with $\alpha = 0.5$ and $\beta = 1$. Each of these two utility functions are calculated for both AD and symmetric distributions for two different conditioning events, $E$ and $F$. The event $E$ is the event that the market return is less than the certainty-equivalent market return, $w_m$, and event $F$ is the event that the market return is lower than the certainty-equivalent market return, $w_m$, less two market return standard deviations.
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We consider two sets of utility parameters: disappointment aversion, given by $\alpha = 0.5$ and $\beta_u = 0.5$, and no disappointment aversion, given by $\alpha = 0.5$ and $\beta_u = 0.5$. We define two events: $E$, the event that the market return is less than the certainty-equivalent market return, $w_m$, and $F$, the event that the market return is less than two market return standard deviations. The density of Equation (1.1) for event $E$ is given in Figure 1.1(a) and (c). If an investor is not disappointment-averse, then their utility is similar regardless of the return distribution for event $E$. The utility of a disappointment-averse investor drops for both AD and symmetric distributions, with lower utility for the AD distribution than the symmetric distribution.

Further into the lower tail, the realizations of the AD distribution are much further away from the certainty equivalent than those of the symmetric distribution. Therefore, the utility of event $F$ is less than that for event $E$. In addition, the utility of the disappointment-averse investor is lower for the AD distribution than for the symmetric distribution (Figure 1.1(b) and (d)). That is, as the level of tail dependence that defines our event, $F$, becomes even more pronounced, an investor displaying aversion to disappointing outcomes will experience lower net utility compared with an investor whose preferences are defined over an event spanning a much wider range of market realizations (event $E$, for example). Furthermore, the characteristics of the joint return distribution will ultimately dictate the value of the certainty equivalent, which in turn impacts the overall level of utility via the weighting $(1 - \alpha)w$. Therefore, to capture economically meaningful AD requires a metric that captures the relative differences in the shape of the dependence in the upper and lower tail.

1.2 FROM SKIAJAS PREFERENCES TO ASSET PRICES

The implication of Skiadas-style preferences is that the ranking of the preferences of an act in a given state depends on the state itself (state-dependence) as well as on the payoffs at other states (non-separability). Following Skiadas (1997), disappointment aversion therefore uniquely satisfies

$$u(b) = A[f(b, u(b))], \quad b \in B,$$

where $u$ is an unconditional utility, $f$ is non-increasing in its last argument representing the conditional utility given some fixed partition, $P$, and $A : L \rightarrow \mathbb{R}$ is an increasing mapping where $L$ is the set of all random variables. Hence, the subjective consequences that define the conditional utility function associated with the outcome of a random lottery are captured by the aggregator function, $A$.

Skiadas (1997) shows that for arbitrary probability, $\mathbb{P}$, the pair $(U, \mathbb{P})$ admits an additive representation if, for every event $D$,

$$b \geq^D c \Leftrightarrow \int_D U(b)d\mathbb{P} \geq \int_D U(c)d\mathbb{P}, \quad b, c \in B.$$

if $U$ is of the form $U : \Omega \times B \rightarrow \mathbb{R}$.

Under certain conditions, the aggregate consequence of these preferences for the realization of a given state results in a pricing kernel adjustment, reflecting the degree to which these preferences represent a departure from expected utility behaviour. To consider the Skiadas preferences in an asset-pricing

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5We retain $\alpha = 0.5$, meaning that although the agent does not display either Skiadas (1997) or Gul (1991) disappointment aversion conditional on $E$, the net utility continues to be a weighted average of the local utility and the certainty equivalent. This implies that if all returns are equal to the asset's certainty equivalent, then $x - w$ in the expression for $\varphi$ is zero. Therefore, $\alpha \varphi = 0$, but $(1 - \alpha)w$ is non-zero, so the agent continues to generate some utility in this instance.
function of the aggregate variables as well as a wealth-consumption ratio. The variable with agents displaying hyperbolic absolute risk aversion,\(^6\) the system of time derived from the solution to the agent’s maximum utility optimization problem:

\[ \beta \]

where \( \beta \) is a constant, \( \pi(a_{t+1} | a_t) \) is the conditional probability of realizing macro state \( a_{t+1} \) given current macro state \( a_t \), \( U_t(c_t, w_t') \) is the contribution of \( (c_t, w_t') \) to the agent’s utility in state \( a_{t+1} \), \( u(c_t) \) is the time-independent utility of date \( t \) and \( V_{t+1}^* \) is the indirect utility function for date \( t + 1 \) realization of wealth, given by

\[ V_{t+1}^*(w_t', a_{t+1}) = \max_{c_{t+1}, w_{t+1} \in B(w_t')} \sum_{a_{t+1} \in \mathcal{A}} \pi(a_{t+1} | a_t) U_t(c_t, w_t', a_{t+1}), \]

where \( B(w_t') \) is the agent’s budget set. The aggregator, \( \varphi_t \), accounts for the date \( t + 1 \) preference states, \( g_t', \ldots, g_t'' \), conditional on attaining macro state \( a_{t+1} \). When the aggregator, \( \varphi_t \), is chosen to be consistent with agents displaying hyperbolic absolute risk aversion,\(^6\) the system of time \((t + 1)\) state-prices can be derived from the solution to the agent’s maximum utility optimization problem:

\[ \phi(a_{t+1} | a_t) = \pi(a_{t+1} | a_t) \bar{M}_{t+1} \]

\[ = \pi(a_{t+1} | a_t) \beta \left( \frac{C_{t+1}}{C_t} \right)^\gamma \left( \frac{R^K_{t+1}}{R^K_t} \right)^\gamma \left[ 1 - \frac{\tilde{\delta}_{t+1}}{\tilde{Q}_{t+1} + 1} \right]^{-\gamma}. \]

Here, \( \bar{M}_{t+1} \) is the state-price deflator, \( C_t \) is aggregate market consumption, \( R^K_t \) is a measure of aggregate relative risk aversion, \( \bar{C}_{t+1} \) and \( \bar{R}^K_{t+1} \) are random variables reflecting aggregate consumption and risk aversion at time \( t + 1 \) conditional upon information at date \( t \), \( \gamma \) and \( \beta \) are constants, and \( \tilde{Q}_{t+1} \) is a function of the aggregate variables as well as a wealth-consumption ratio. The variable \( \tilde{\delta}_{t+1} \equiv \delta(a_{t+1} | a_t) \) is a state-dependent function representing the aggregate departure from expected utility behaviour. With \( \tilde{\delta}_{t+1} \equiv 0, \bar{M}_{t+1} \) reduces to the Lucas (1978) model under certain simplifying assumptions on the relation between aggregate risk aversion and aggregate consumption.

If, in Equation (1.6), we set \( \delta(a_{t+1} | a_t) = f(g_t', \ldots, g_t'') \), where \( f \) is defined in Equation (1.4), we see that deviations from expected utility depend on the collective incremental experiences associated with state \( a_{t+1} \) being realized. This observation has several implications for measuring AD, in that any measure of AD will need to suppose that two incremental characteristics matter for asset pricing. First, it must measure AD over and above the level of dependence that is consistent with ordinary beta. This supposes that an incremental risk premium may be required to hold an asset that displays LTAD with the market beyond what would typically be expected if the assets were jointly normal. The consequence of holding a tail-dependent asset is that the investor experiences a sense of disappointment that losses are larger than what the market is prepared to compensate for. Second, any measure of

\(^6\)Chosen by Kraus and Sagi (2006) for tractability.
AD must incorporate differences in tail dependence across the upper and lower tail. This is consistent with an investor preferring UTAD to LTAD, as a stock with UTAD is more likely to recover the initial loss associated with market drawdowns in the event that the market subsequently bounces. The consequence of the investor holding a LTAD asset can therefore be expected to elicit a sense of disappointment that they did not invest in a stock with compensating characteristics (i.e., UTAD) given the drawdown event.

1.3 CONSISTENTLY MEASURING ASYMMETRIC DEPENDENCE

To measure the relevant characteristics embodied within Skiadas’s framework of preferences, we propose a metric that captures the asymmetry of dependence in the upper and lower tail, across a range of market events, over and above the level of dependence that is consistent with ordinary beta. We measure AD using an adjusted version of the $J$ statistic, originally proposed by Hong et al. (2007). $J_{\text{Adj}}$ is a non-parametric and $\beta$-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 extreme value theory (Poon et al., 2004), higher-order moments (Harvey and Siddique, 2000), downside beta (Ang et al., 2006), copula function parameters (Genest et al., 2009; Low et al., 2013) and the $J$ statistic itself. However, many of these metrics have difficulty capturing the level and price of AD in asset return distributions independently of other price-sensitive factors such as the CAPM beta.

To illustrate, we concoct an approximate AD distribution by simulating $N = 25,000$ pairs of random variables $(x, y)$ where $x_i \sim N(\mu_S, \sigma_S)$ and $y_i = \beta x_i + \epsilon_i$, where $\epsilon_i \sim N(0, (x_i + \mu_S)^\alpha)$, with $\mu_S = 0.25$ and $\sigma_S = 0.15$. When $\alpha = 0$, no AD is present and $(x, y)$ are bivariate normal with linear dependence equal to $\beta$. Higher LTAD is proxied by increasing $\alpha > 0$, and higher UTAD is proxied by decreasing $\alpha < 0$. A sample of $N = 500$ simulated data points is given in Figure 1.2.

![Simulated Asymmetric Dependence Data](image)

(a) Asymmetric dependence

![Simulated Symmetric Dependence Data](image)

(b) Symmetric dependence

FIGURE 1.2 Scatter plot of simulated bivariate data with asymmetric dependence (a) and symmetric dependence (b) that is used to test different downside-risk metrics. The $N = 500$ sample is a random draw of bivariate data $(x, y)$ where $x_i \sim N(\mu_S, \sigma_S)$ and $y_i = \beta x_i + \epsilon_i$, where $\epsilon_i \sim N(0, (x_i + \mu_S)^\alpha)$, with $\mu_S = 0.25$, $\sigma_S = 0.15$ and $\beta = 2.0$. In (a), $\alpha = 2$ so the sample displays LTAD. In (b), $\alpha = 0$ so no AD is present and $(x, y)$ are bivariate normal with linear dependence equal to $\beta$. Higher LTAD is proxied by increasing $\alpha > 0$, and higher UTAD is proxied by decreasing $\alpha < 0$. 
Ordinary least-squares estimates of the CAPM beta and the downside beta, and IFM estimates of the Clayton copula parameter of LTAD, are provided in Figure 1.3 for various combinations of $\alpha$ and $\beta$.

The CAPM beta and the 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 $\alpha$. Almost all Archimedean copulae, including multi-parameter copulae, will similarly be unable to determine AD separately 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.

Further, downside and upside $\beta$s are also likely to be confounded with the CAPM $\beta$, so that any risk premium empirically associated with downside $\beta$, upside $\beta$, or even the difference in upside and downside $\beta$, is likely to reflect both the compensation for systematic risk and asymmetries in upside and downside risk. Ang et al. (2006) are careful to avoid this confounding by ensuring that the CAPM $\beta$ and the upside/downside $\beta$s are not included in the same cross-sectional regression.

### 1.3.1 The Adjusted J Statistic

The $J$ statistic of Hong et al. (2007) is able to identify AD and allows the use of critical values to establish a hypothesis test on the presence of AD. We introduce the $\beta$-invariant adjusted $J$ statistic, in order to establish the AD premium separately from the CAPM $\beta$ premium while retaining the integrity of the dependence structure. We obtain $\beta$-invariance by unitizing $\beta$ for each data set before a modified version of the $J$ statistic is computed. In particular, given $(R_{it}, R_{mt})_{i=1}^{T}$ (Figure 1.4(a)), we first let $\hat{R}_i = R_i - \beta R_m$ (Figure 1.4(b)), where $R_i$ and $R_m$ are the continuously compounded return on the $i$th asset and the market, respectively, and $\hat{\beta}_{R_i R_m} = \text{cov}(R_i, R_m)/\sigma_{R_i}^2$. This initial transformation sets $\beta_{R_i R_m} = 0$, making it possible to standardize the data without contaminating the linear relation between the variables (Figure 1.4(c)). Standardization yields $\hat{R}_{it}^\circ$ and $\hat{R}_{mt}^\circ$ and ensures that the standard deviation of the market model residuals, a measure of idiosyncratic risk, is identical for all data sets. We then re-transform the data to have $\hat{\beta}_{R_i R_m} = 1$ by letting $\tilde{R}_i = R_i^\circ$ and $\tilde{R}_m = \hat{R}_{it}^\circ + \hat{R}_{mt}^\circ$ (Figure 1.4(d)). Therefore, all data display the same $\beta$ after these transformations, forcing the output of $J^{adj}$ to be invariant to the overall level of linear dependence, as well as being independent of idiosyncratic risk.

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7For full details of the inference function for margins (IFM) method of estimating copula parameters, see Joe (1997).

8The unadjusted $J$ statistic of Hong et al. (2007) is similar to the difference between upside and downside beta, $\beta^u - \beta^d$, if only one exceedance ($\delta = 0$) is used. The notable difference is that the $J$ statistic determines the squared differences in correlations, whereas the upside/downside $\beta$s scale the unsquared differences by market semi-variance. The adjustment of the $J$ statistic, described in Section 1.3.1, removes the influence of $\beta$ altogether.

9We are careful to avoid look-ahead bias by ensuring that at time $t$, only historical data up to time $t$ is employed to estimate the $\hat{\beta}_{R_i R_m}$ used to standardize the data.

10From the market model, the total variance of a stock’s returns can be written as $\sigma_t^2 = \beta^2 \sigma_M^2 + \sigma_e^2$, where $\sigma_M^2$ is the market’s variance and $\sigma_e^2$ is the variance of the idiosyncratic component of returns. Since we set $\beta = 0$, $\sigma_t^2 = \sigma_e^2$. Hence, standardizing at this point is equivalent to dividing out the idiosyncratic component of transformed returns.

11At this point, $R_m \sim N(0, 1)$ whereas $\hat{R}_d \sim N(0, \sqrt{2})$ assuming marginal distributions are normal. This holds for all stocks.
Disappointment Aversion, Asset Pricing and Measuring Asymmetric Dependence

(a) CAPM beta estimates for $\alpha = 0$, $\beta \in (-0.75, 0.75)$

(b) CAPM beta estimates for $\beta = 1$, $\alpha \in (-0.75, 0.75)$

(c) CAPM beta estimates for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$

(d) Downside beta estimates for $\alpha = 0$, $\beta \in (-0.75, 0.75)$

(e) Downside beta estimates for $\beta = 1$, $\alpha \in (-0.75, 0.75)$

(f) Downside beta estimates for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$

(g) Clayton copula parameter estimates for $\alpha = 0$, $\beta \in (-0.75, 0.75)$

(h) Clayton copula parameter estimates for $\beta = 1$, $\alpha \in (-0.75, 0.75)$

(i) Clayton copula parameter estimates for $\alpha = 0.5$, $\beta \in (-0.75, 0.75)$

**FIGURE 1.3** Estimates of linear dependence and AD. We estimate the CAPM beta, downside beta and the Clayton copula parameter using $N = 10,000$ simulated pairs of data $(x, y)$, where $y = \beta x + \epsilon$, with $x \sim N(0.25, 0.15)$ and $\epsilon \sim N(0, (x + 0.25)\alpha)$. Higher levels of linear dependence are incorporated with higher values of $\beta$ and higher levels of LTAD are incorporated with higher levels of $\alpha$. Figure parts (a), (d) and (g) provide estimates for varying levels of linear dependence but with no AD ($\alpha = 0$). Figure parts (b), (e) and (h) provide estimates for varying degrees of AD with constant linear dependence ($\beta = 1$). Figure parts (c), (f) and (i) provide estimates for varying degrees of linear dependence with constant AD ($\alpha = 0.5$).
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Figure 1.4: Data transformations. To calculate the $J^{Adj}$ statistic with a random sample, \( \{ R_{it}, R_{mt} \}_{t=1}^{T} \), as in (a), we let $\hat{R}_i = R_i - \hat{\beta} R_{mt}$ where $R_i$ is the continuously compounded return on the $i$th asset, $R_{mt}$ is the continuously compounded return on the market and $\hat{\beta} = \text{cov}(R_i, R_{mt})/\sigma^2_{R_{mt}}$. This transformation forces $\hat{\beta}_i R_{it}, R_{mt} = 0$, as in (b). We standardize the transformed data, yielding $\hat{R}_{mi}$ and $\hat{R}_{si}$ in (c). Finally, we re-transform the data to have $\hat{\beta} = 1$ by letting $\tilde{R}_{mi} = \hat{R}_{mi}$ and $\tilde{R}_{si} = \hat{R}_{si} + \hat{R}_{mi}$ in (d).

The solid line through the middle of each plot is given to illustrate how the linear trend changes with each transformation.

\[ J^{Adj} \text{ is given by } \]
\[ J^{Adj} = [\text{sign}(\hat{\beta}^+ - \hat{\beta}^-)]^T (\hat{\beta}^+ - \hat{\beta}^-)^T \hat{\Omega}^{-1} (\hat{\beta}^+ - \hat{\beta}^-). \]

(1.7)

for $\hat{\beta}^+ = \{ \hat{\beta}^+(\delta_1), \hat{\beta}^+(\delta_2), \ldots, \hat{\beta}^+(\delta_N) \}$ and $\hat{\beta}^- = \{ \hat{\beta}^-(\delta_1), \hat{\beta}^-(\delta_2), \ldots, \hat{\beta}^-(\delta_N) \}$, where $I$ is an $N \times 1$ vector of ones, $\hat{\Omega}$ is an estimate of the variance–covariance matrix (Hong et al., 2007) for the difference vector $(\hat{\beta}^+ - \hat{\beta}^-)$ and

\[ \hat{\beta}^+(\delta) = \text{corr} (\tilde{R}_{mi}, \tilde{R}_{ij} | \tilde{R}_{mi} > \delta, \tilde{R}_{ij} > \delta), \]

(1.8)

\[ \hat{\beta}^-(\delta) = \text{corr} (\tilde{R}_{mi}, \tilde{R}_{ij} | \tilde{R}_{mi} < -\delta, \tilde{R}_{ij} < -\delta). \]

(1.9)
Estimates of linear dependence and AD. We estimate the

\[ J \]

\[ \beta \]

\[ \xi \]

\[ N \]

\[ V \]

\[ \chi \]

\[ \rho \]

\[ \alpha \]

\[ \beta \]

\[ \delta \]

\[ \gamma \]

\[ \epsilon \]

\[ \xi \]

\[ N \]

\[ V \]

\[ \chi \]

\[ \rho \]

\[ \alpha \]

\[ \beta \]

\[ \delta \]

\[ \gamma \]

\[ \epsilon \]

\[ \xi \]

\[ N \]

\[ V \]

\[ \chi \]

\[ \rho \]

\[ \alpha \]

\[ \beta \]

\[ \delta \]

\[ \gamma \]

\[ \epsilon \]

\[ \xi \]

\[ N \]

\[ V \]

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\[ \alpha \]

\[ \beta \]

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\[ \alpha \]

\[ \beta \]

\[ \delta \]

\[ \gamma \]

\[ \epsilon \]

\[ \xi \]

\[ N \]

\[ V \]

\[ \chi \]

\[ \rho \]

\[ \alpha \]

\[ \beta \]

\[ \delta \]

\[ \gamma \]

\[ \epsilon \]

\[ \xi \]

\[ N \]

\[ V \]

\[ \chi \]

\[ \rho \]

\[ \alpha \]

\[ \beta \]

\[ \delta \]

\[ \gamma \]

\[ \epsilon \]

\[ \xi \]
J^{Adi} captures both LTAD and UTAD between a stock and the market. To isolate upside and downside risk for the purposes of our regression analysis, we compute

\[ J^{Adi}_+ = J^{Adi}_{|J^{Adi}>0}, \]

\[ J^{Adi}_- = J^{Adi}_{|J^{Adi}<0}. \]

We capture a family of conditional preferences, consistent with those of the Skiadas agent, by employing a range of exceedances in the calculation of \( J^{Adi} \). Adjusting \( J \) to be \( \beta \)-invariant enables identification of the price paid by disappointment-averse agents in addition to the ordinary \( \beta \) risk premium. \( J^{Adi}_- \) and \( J^{Adi}_+ \) capture disappointment and elation premia distinctly.

Further, as a non-parametric measure of AD, the \( J^{Adi} \) statistic facilitates the separation of the actual price of tail dependence from the effect of non-normal marginal return characteristics. \( J^{Adi} \) is also consistent with the work of Stapleton and Subrahmanyam (1983) and Kwon (1985), who suggest a means of deriving a linear relation between \( \beta \) and expected return without the need for multivariate normal assumptions. \( J^{Adi} \) is also consistent with the evidence that correlations tend to be larger in the lower tail of the joint return distribution compared with the upper tail (Longin and Solnik, 2001; Ang and Chen, 2002). LTAD exists provided that 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.

Another 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 (and despite) the debate over whether idiosyncratic risk is relevant in an asset-pricing context (Goyal and Santa-Clara, 2003; Bali et al., 2005). It is sometimes argued that idiosyncratic risk should be priced whenever investors fail to hold sufficiently diversified portfolios (Merton, 1987; Campbell et al., 2001; Fu, 2009). However, when tail risk is characterized by dependence that increases during down markets, the ability to diversify will be affected 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 increase 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 analysing 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.

1.4 SUMMARY

Skiadas (1997) offers an alternative framework to the standard von Neumann–Morgenstern expected utility theory, 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.

Individuals with Skiadas preferences are 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 agent’s 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 the event.

We demonstrate that AD influences the utility of disappointment-averse investors and establish the conditions under which this implies a market price for LTAD and UTAD. Using a comprehensive
set of simulations, we demonstrate that many of the commonly employed risk metrics are unable to adequately capture the salient distributional characteristics of AD. We further propose a $\beta$-invariance metric to capture AD consistent with Skiadas preferences and demonstrate its suitability using simulated AD data sets.

REFERENCES


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FURTHER READING


