On the cross-sectional asymmetric dependence between investment returns

Petra Andrlikova

The University of Sydney Business School

Finance Discipline

A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

2019

Abstract

The benefits of diversification decrease substantially during market downturns due to asymmetric dependence between stock and market returns. Not all assets are affected in the same way. This thesis provides a substantial evidence of the cross-sectional variation in asymmetric dependence between equity returns and market returns across the 38 largest financial markets and a variety of asset classes.

I document that asymmetric dependence between stock returns and market returns is significantly priced in international equity returns. Of all the commonly considered factors, asymmetric dependence is the only factor that is priced in all 38 markets examined. Internationally, investors require additional compensation to hold assets displaying asymmetric dependence. Notably, the degree of asymmetric dependence increases faster in countries experiencing stronger growth in their financial markets. This thesis supports recognition of asymmetric dependence as a risk factor that has significant implications for, inter alia, asset pricing, cost of capital, and performance evaluation.

Moreover, I build a general equilibrium model to identify important drivers of the cross-sectional variation in asymmetric dependence. I show that stocks with a high level of fundamental cash-flow risk exhibit a large amount of time variation in conditional betas and a relatively higher degree of the cross-sectional asymmetric dependence. The asymmetric effects of heterogeneous cash-flow risk on the cross section of return dependence are driven by preference shocks correlated with the business cycle. The model predictions are confirmed by US industry data.

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor Dr. Jamie Alcock for the continuous support of my Ph.D study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis.

Besides my advisor, I would like to thank my academic mentors: Prof. Michael Gallmeyer and Dr. Timothy McQuade for their insightful comments and support, which led me to write my job market research paper and incented me to widen my research from various perspectives.

My sincere thanks also goes to Professor Jens Jackwerth and Professor Andrew Baum, for their precious support in providing me with an opportunity to visit them at the Konstanz University and Oxford University.

A special thanks to my family. Words cannot express how grateful I am to my mother for all of your support that led me to strive towards my goal. At the end, I would like express appreciation to my beloved partner Marek Sinagl who gave me all the strength I needed to be able to finish this thesis.

Declaration

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

The work that forms the basis of Chapter 2.2 and Chapter 4 has been published as follows:

Jamie Alcock and Petra Andrlikova. Asymmetric dependence in real estate investment trusts: An asset-pricing analysis. *The Journal of Real Estate Finance and Economics*, 56(2):183-216, 2018.

The work that forms the basis of Chapter 3 is co-authored with my advisor Dr. Jamie Alcock. I am the corresponding author of this work.

Petra Andrlikova

July, 2019

Contents

List of Figures

List of Tables

1

Introduction

Asymmetric Dependence 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 (Patton, 2004) - see Figure 1(a). Investors may well exhibit preferences for certain types of AD. For example, consider two stocks A and B that have identical β and equal average returns. Stock A exhibits a higher correlation in the lower tail of excess returns whilst stock B is symmetric in return dependence. 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 βs, are equal. However, investors may prefer stock B over A since stock A is more likely to suffer abnormal losses during any market downturn.

Many authors find evidence for the existence of AD in US stock equities. See, for example, Ang and Bekaert (2002); Ang, Hodrick, Xing, and Zhang (2006b); Campbell, Koedijk, and Kofman (2002); Chabi-Yo, Ruenzi, and Weigert (2017); Hartmann, Straetmans, and De Vries (2004); Jiang, Wu, and Zhou (2017); Kelly and Jiang (2014); Knight, Satchell, and Tran (1995); Oh and Patton (2017); Patton (2004); Weigert (2015). In addition, several of these studies identify the existence of AD between well-diversified stock indices, thereby providing credible evidence that AD is not easily diversified.

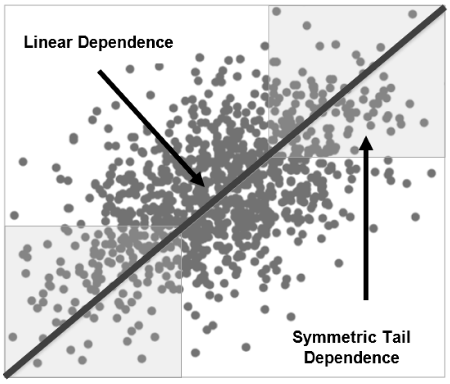
If investors exhibit preferences with respect to AD then I expect AD to be priced in financial markets if, in addition, it exists and is non-diversifiable. Disappointment averse investors with state-dependent preferences, such as those described by Skiadas (1997), will demand a return premium to compensate for lower-tail asymmetric dependence exposure (Figure 1a). With a significant risk premium for AD, the cost of capital will be substantially underestimated if AD is not incorporated properly.

Asymmetric dependence is heavily priced in the cross section of US listed equities (Alcock and Hatherley, 2016; Ang, Chen, and Xing, 2006a). The premium associated with AD is consistent with disappointment-averse investors, such as those described by Skiadas (1997), who expect an additional premium as compensation for the asymmetric dependence risk. However, to date, little is known about why AD exists, whether AD is a risk-based factor, and whether the pricing of AD is US-centric or an international phenomenon. The focus of this thesis is to provide answers to these questions.

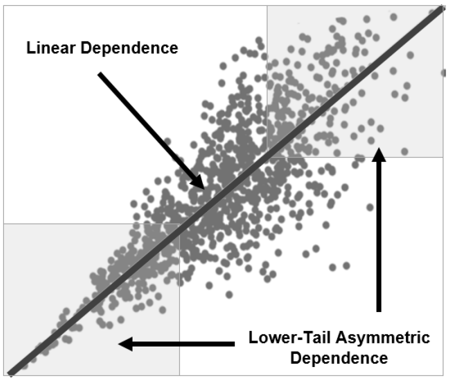
Asymmetric dependence has important implications not only for asset pricing but also for cost of capital estimation, capital allocation, performance management and executive compensation. The phenomenon of asymmetric dependence, its importance for international investors and its main determinants has not been sufficiently explored. This thesis fills in this gap and provides evidence that asymmetric dependence is priced internationally and across a range of different asset classes.

This thesis is structured as follows. In Chapter 2, I describe the empirical measure of the cross-sectional asymmetric dependence and discuss the advantages

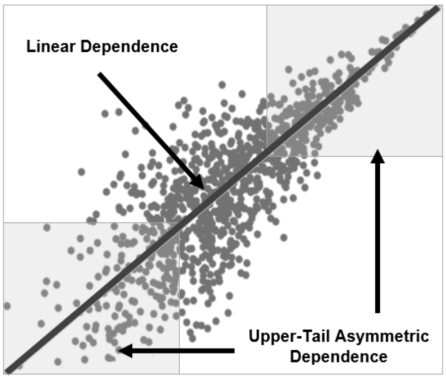
Types of Return Dependence



(a) Symmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 1.1: Scatter plot of simulated bivariate data with different types of dependence. The dependence between stock excess returns and market excess returns may be described by a linear component (CAPM β) and a higher-order components, capturing 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. Panels (1.1(a)) to (1.1(c)) display three possible types of return dependence, symmetric dependence, lower-tail asymmetric dependence and upper-tail asymmetric dependence.

of the particular empirical measure of AD that is used in this thesis. Next, in Chapter 3, I show that asymmetric dependence is priced internationally across all the 38 largest financial markets. Moreover, in Chapter 4, I find that asymmetric dependence exists also among US listed real-estate equities that are commonly considered as defensive assets. All the previous chapters provide empirical evidence of the cross-sectional asymmetric dependence between equity returns without discussing where asymmetric dependence may come from. Chapter 5 provides a theoretical framework that identifies the heterogeneous cash-flow risk of firms as an important driver of the cross-sectional asymmetric dependence.

I measure the cross-sectional asymmetric dependence using the Alcock and Hatherley (2016) J^{Adj} statistic, which is, to the best of my knowledge, the only metric that is able to measure asymmetric dependence orthogonally from linear dependence. I use the J^{Adj} statistic to identify the level of AD of individual equity returns, because this metric provides a monotonic measure in AD that allows for the pricing of AD independently of the price of β risk. The resulting price of AD measured using the J^{Adj} statistic then corresponds to the additional return premium that investors request to bear the asymmetric dependence risk, over and above any premia that may be attached to β or idiosyncratic risk. Many of the existing studies explore dependence using a single measure, thereby capturing both the symmetric, linear dependence and AD with the same metric. From an asset pricing perspective and for the purposes of cost of capital estimation, it is important to separate these factors to identify the price of AD orthogonally to the price of linear, market (β) risk, which is achieved when the J^{Adj} statistic is used.

In Chapter 3, I contribute to a greater understanding of AD by showing both its existence and pricing is an international phenomenon. I find that the average level of lower-tail asymmetric dependence and upper-tail asymmetric dependence[1] among most markets examined is stronger than that found in the US market.

The international evidence for AD premia is striking; I show that AD is significantly priced in all stock markets examined. Among commonly considered factors, I find that asymmetric dependence is the only factor that is consistently priced in-sample across all markets considered. My findings are consistent with asymmetric dependence being a risk-based factor (see Griffin (2002)) that affects excess equity returns internationally. In addition, I find that the degree of AD strengthens in countries experiencing faster growth in their financial markets. Similarly, the proportion of firms exhibiting LTAD increases as financial markets grow in size and importance. This has important implications for financial market stability, because growth in national market capitalization relative to GDP may be associated with negative effects for the real economy, ie potential abnormal losses experienced during market downturns.

In Chapter 4, I explore the empirical evidence of the existence of AD across US listed real-estate investment trusts (REITs). REITs are often assumed to be defensive assets having a low correlation with market returns. However, this dependence is not symmetric across the joint-return distribution. Disappointment-averse investors with state-dependent preferences attach (dis-)utility to investments exhibiting (lower-tail) upper-tail asymmetric dependence. I find strong empirical evidence that investors price this asymmetric dependence in the cross section of US REIT returns. In particular, I show that REIT stocks with lower-tail asymmetric dependence attract a risk premium averaging 1.3 % p.a. and REIT stocks exhibiting upper-tail asymmetric dependence are traded at discount averaging 5.8

[1]Lower- (upper-) tail asymmetric dependence describes a situation when a stock return correlation with market returns is higher during market downturns (upturns) relative to upturns (downturns), as illustrated in Figure 1.1.

% p.a. I find no evidence that the equity β is positively priced in US REIT returns. These findings imply that traditional estimators of REIT cost of capital and performance measurement are likely to be substantially misrepresentative.

The identification of assets with a relatively low return dependence in bad states (diversification) and a high dependence in good states (abnormal gains) is very attractive for investors. Alcock and Hatherley (2016) show that a relatively high (low) correlation of stock returns with market returns in bad times relative to good times is associated with a significant return premium (discount). It still remains unclear, however, why the cross-sectional variation in AD exists or which stocks are more likely to exhibit a high degree of AD and perform relatively worse during market downturns.

Moreover, despite a large body of empirical evidence identifying the cross-sectional variation in asymmetric dependence between stock and market returns,[1] little is known about the drivers of these cross-sectional differences. In Chapter 5 of this thesis, I provide a theoretical explanation for the existence of the cross-sectional asymmetric dependence. The benefits of diversification decrease substantially during market downturns due to asymmetric dependence between stock and market returns. Not all assets are affected in the same way. I build a general equilibrium model to show that stocks with a high level of fundamental cash-flow risk exhibit a large amount of time variation in conditional betas and a relatively higher degree of asymmetric dependence. The asymmetric effects of heterogeneous cash-flow risk on the cross section of return dependence are driven by preference shocks correlated with the business cycle. The model predictions are confirmed by data.

[1] See, for example, Alcock and Hatherley (2016); Ang and Bekaert (2002); Ang et al. (2006b); Campbell et al. (2002); Chabi-Yo et al. (2017); Hartmann et al. (2004); Kelly and Jiang (2014); Knight et al. (1995); Patton (2004); Weigert (2015).

2

Describing The Cross-sectional Asymmetric Dependence

2.1 Measuring Asymmetric Dependence

Multiple measures exist that attempt to capture asymmetric dependence and/or downside tail risk (the downside β (Ang et al., 2006a), Archimedean copula (Genest et al., 2009), H-statistic (Ang and Chen, 2002), the J-statistic (Hong et al., 2007) and the Alcock and Hatherley (2016) adjusted-J statistic). The Alcock and Hatherley (2016) J^{Adj} statistic is the only metric that is able to measure asymmetric dependence orthogonally from linear dependence. I use the J^{Adj}-statistic to identify the level of AD of individual equity returns, because this metric provides a monotonic measure in AD that allows for the pricing of AD independently of the price of β risk.

The alternative metrics of asymmetric dependence typically use a single measure and thereby capture both the symmetric, linear dependence, and AD with the same statistic. From an asset-pricing perspective and for the purposes of my study, it is important to separate these factors to identify the price of AD orthogonally to the price of linear, market (β) risk.

I quantify the degree of asymmetric dependence between stock returns and market returns using the Alcock and Hatherley (2016)'s Adjusted J-statistic (J^{Adj}). This measure of AD is orthogonal to the systematic and idiosyncratic risk.

Defining the J^{Adj} Statistic

The Adjusted J-statistic (J^{Adj}) adapts the J statistic proposed by Hong et al. (2007) so that it is β and idiosyncratic risk invariant, thereby improving its utility in empirical asset-pricing studies. The J^{Adj} is defined by Alcock and Hatherley (2016) as

$$AD = J^{Adj} = \left[\text{sgn}\left(\left[\tilde{\rho}^{+} - \tilde{\rho}^{-}\right]\mathbf{1}'\right) T \left(\tilde{\rho}^{+} - \tilde{\rho}^{-}\right)' \hat{\Omega}^{-1}(\tilde{\rho}^{+} - \tilde{\rho}^{-})\right], \tag{2.1}$$

where $\tilde{\rho}^{+} = \{\tilde{\rho}^{+}(\delta_1), \tilde{\rho}^{+}(\delta_2), ..., \tilde{\rho}^{+}(\delta_N)\}$ and $\tilde{\rho}^{-} = \{\tilde{\rho}^{-}(\delta_1), \tilde{\rho}^{-}(\delta_2), ..., \tilde{\rho}^{-}(\delta_N)\}$, $\mathbf{1}$ is $N \times 1$ vector of ones, $\hat{\Omega}$ is an estimate of the variance-covariance matrix, (Hong et al., 2007). The conditional correlations are defined as follows, for $\delta_j \in \{\delta_1, ..., \delta_N\}$,

$$\tilde{\rho}^{+}(\delta_j) = \text{corr}\left(\tilde{R}_{mt}, \tilde{R}_{it} | \tilde{R}_{mt} > \delta_j, \tilde{R}_{it} > \delta_j\right) \tag{2.2}$$

$$\tilde{\rho}^{-}(\delta_j) = \text{corr}\left(\tilde{R}_{mt}, \tilde{R}_{it} | \tilde{R}_{mt} < -\delta_j, \tilde{R}_{it} < -\delta_j\right). \tag{2.3}$$

With symmetric dependence the value of J^{Adj} will be close to zero. A significant and non-zero value of J^{Adj} provides evidence of an asymmetry between the lower and upper-tail dependence.

I replicate the procedure proposed by Alcock and Hatherley (2016) to estimate the Adjusted J-statistic (J^{Adj}) for each equity in each country individually. First, for each set $\{R_{it}, R_{mt}\}_{t=1}^{T}$, I get $\hat{R}_{it} = R_{it} - \beta R_{mt}$, where R_{it} and R_{mt} is the excess return on asset i and market, and $\beta = \text{cov}(R_{it}, R_{mt})/\sigma^2_{R_{mt}}$. The first transformation implies that each data set has a zero CAPM β, $\beta_{\hat{R}_{it},R_{mt}} = 0$. Second, I standardize the data to get identical standard deviation of the CAPM regression residuals and get R^S_{mt} and $\hat{R}^S_{it}$. Third and the final transformation step sets the $\hat{\beta}$ to 1 by letting $\tilde{R}_{mt} = R^S_{mt}$ and $\tilde{R}_{it} = \hat{R}^S_{it} + R^S_{mt}$. After this transformation, all data sets have the same β and standard deviation of model residuals, which compels the J-statistic to be invariant to the linear dependence and the level of idiosyncratic risk.

I estimate the J^{Adj}-statistic using daily excess returns following the definition from equation (5.40) and using the following levels of exceedances

$$\delta = \{0, 0.2, 0.4, 0.6, 0.8, 1\}, \tag{2.4}$$

consistent with Hong et al. (2007) and Alcock and Hatherley (2016).

Separating Lower-tail and Upper-tail Asymmetric Dependence

Consistent with Alcock and Hatherley (2016), I separate the UTAD and LTAD using indicator function $\mathbb{I}_c$, which takes a value of 1 when condition c is satisfied and zero otherwise. Any positive value ($J^{Adj} > 0$) indicates upper-tail asymmetric dependence (UTAD), while a negative value of ($J^{Adj} < 0$) denotes lower-tail asymmetric dependence (LTAD).

$$LTAD = J^{Adj}\mathbb{I}_{J^{Adj}>0} \tag{2.5}$$

$$UTAD = J^{Adj}\mathbb{I}_{J^{Adj}<0} \tag{2.6}$$

I employ this measure for the following reasons. First, I seek to determine the price and level of AD independently of systematic and idiosyncratic risk. The J^{Adj} is, by construction, orthogonal to the CAPM β and the idiosyncratic risk of stock returns. The resulting price of AD measured using the J^{Adj} statistic then corresponds to the additional return premium that investors request to bear the asymmetric dependence risk, over and above any premia that may be attached to β or idiosyncratic risk.

The J^{Adj} statistic differs from, for example, GARCH models that can only characterize the correlation structure but cannot capture higher-order dependence, or Copula functions can explain higher-order dependence but cannot achieve this independently of β and idiosyncratic risk. Weigert (2015) attempts to ameliorate the impact of this issue by conditionally combining different copulae functions, which leads to conditional β being characterized but his tail dependence measures remain compounded by the effects of CAPM β and idiosyncratic risk. Similarly, Ang and Chen (2002)'s downside and upside β cannot separate the effect of asymmetric dependence from linear dependence or idiosyncratic risk on firm excess returns.

Second, I quantify the premia attached to different types of asymmetric dependence. I distinguish between the situation when the return correlation is relatively higher in the lower tail (lower-tail asymmetric dependence) or in the upper tail (upper-tail asymmetric dependence), see Figure 1.1. These two return characteristics have different implications for investors. Stock returns that exhibit lower-tail asymmetric dependence (LTAD) are likely to be associated with a return premium as investors may feel disappointed to hold assets that are highly correlated with the market when the market is down. The upper-tail asymmetric dependent (UTAD) stock returns will likely, on the other hand, be related with a return discount as investors will feel rather elated to hold assets highly correlated with the market in good times.

The J^{Adj} statistic is a model-free nonparametric measure of dependence asymmetries in the data. AD (measured by J^{Adj}) differs from co-skewness, co-kurtosis or upside and downside β measures. The J^{Adj} statistic contains information about all the higher-order co-moments, whereas co-skewness or co-kurtosis correspond to the third and fourth co-moment only. The J^{Adj} measure is different from conditional βs because the J^{Adj} is a function of the differences between the lower and upper-tail correlations, where tail correlations are determined using multiple reference points. Upside and downside βs have only one reference point (typically zero or the mean value), do not measure correlation asymmetries and are not orthogonal to the CAPM β. In order to illustrate the additional informational content (or the importance) of AD, as measured by the J^{Adj}, for investors, I include co-skewness, co-kurtosis, downside and upside βs in my pricing regressions as control variables. For further details about the J^{Adj} statistic, please refer to Alcock and Hatherley (2016).

2.2 The Price of Asymmetric Dependence and Disappointment Aversion

It has long been recognized that investors care differently about downside losses than they do about upside gains (Ang et al., 2006a). This concept has progressed significantly from the classical notion of risk-aversion. Disappointment aversion is distinct from risk-aversion in that disappointment (or elation) violates separability axioms that impose independence across states. That is, outcomes in events that did not occur affect attitudes towards outcomes that did (Grant, Kajii, and Polak, 2001). Several authors develop the theoretical underpinnings of these preferences, including Gul (1991), Grant and Kajii (1998) and Skiadas (1997), all of whom axiomatically model disappointment aversion.

Under the Skiadas model of disappointment aversion, an individual is endowed with a family of conditional preference relations, one for each event. Grant et al. (2001) elegantly describe this as follows:

> *Suppose acts f and g yield the exact same outcomes on event E, but overall (unconditionally) g is preferred to f. Then, if the individual dislikes disappointment, since all else is equal by construction, she will be less unhappy in the event E if she chose f than if she chose g. That is, conditional on E, she prefers f to g. Skiadas defines such an agent as disappointment averse.*

For example, consider two stocks X and Y that have equal CAPM βs and expected returns. Let us further assume that Stock X displays a LTAD with the market, whereas the returns on stock Y follows a multivariate Normal (MVN) distribution with the market (i.e. symmetric dependence), as is described in Figure 1.1. Under the standard assumptions of the CAPM, a risk-averse investor will be indifferent to investments in X or Y. However in the event of a major market drawdown, such as during the 2007-2008 financial crisis, a disappointment-averse investor may prefer stock Y over stock X since stock X is more likely to suffer losses in a situation when investors' wealth is already low. This disappointment translates to investor dis-utility, and so disappointment-averse investors may demand a return premium in order to compensate them for the dis-utility associated with LTAD. Similarly, elation-seeking investors may accept a return discount in return for the greater utility derived from UTAD.

The depiction of disappointment-averse investors having a family of conditional preference relations is the distinguishing feature of the Skiadas (1997) framework. This insight recognises that an agent may, for example, experience significant disappointment in the event of an extreme market drawdown and little or no disappointment in the event of a slight market drawdown. In the following section, I describe a metric of AD that is designed to capture a family of conditional preferences, as described by Skiadas (1997). In contrast, Gul endows investors with a single Savage preference relation and denotes disappointment relative to the certainty equivalent of the investment return distribution. Ang et al.'s (2006a) downside β is motivated by Gul's (1991) description of disappointment aversion. For completeness, I compare the primary results with those found using downside β in Section 4.5.

Ang et al. (2006a) 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 down-weighted relative to outcomes that lie below the reference point (disappointing outcomes). The disappointment-averse utility function is therefore defined as:

$$\phi(x,\nu) = \begin{cases} u(x) & \text{for } x \text{ satisfying } u(x) \le \nu \\ \frac{u(x)+\beta\nu}{1+\beta} & \text{for } x \text{ satisfying } u(x) > \nu, \end{cases} \tag{2.7}$$

where u is a generic utility function, β is the coefficient of disappointment aversion, and ν 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.[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:

$$\left(x = y \,\text{on}\, F \,\text{and}\, y \succeq^{\Omega} x\right) \Rightarrow x \succeq^{F} y, \quad x, y \in X, \tag{2.8}$$

where Ω 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 fam-

[1]The set of preferences (u, β) satisfying (2.7), are risk averse if and only if $\beta \geq 0$ and u is concave (see Gul (1991), Theorem 3 for proof). Furthermore, (u_1, β_1) is more risk averse than (u_2, β_2) if $\beta_1 \geq \beta_2$ and $R^a_{u_1}(x) \geq R^a_{u_2}(x)$ for all x, where $R^a_u(x) = -u''(x)/u'(x)$, the coefficient of absolute risk aversion (see Gul (1991), Theorem 5 for proof). It follows that if (u_1, β_1) is more risk averse than (u_2, β_2), 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 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.

ily of conditional preference relations, one for each event (Grant and Kajii, 1998). 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 (2.8) has two important implications for my 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 (2.8) 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. I therefore 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. (2006a) show that investors require higher compensation to invest in stocks that are sensitive to market downturns.

3

The Price of Asymmetric Dependence: International Evidence

This chapter contributes to a greater understanding of AD by showing both its existence and pricing is an international phenomenon. I find that the average level of lower-tail asymmetric dependence and upper-tail asymmetric dependence[1] among most markets examined is stronger than that found in the US market. In addition, the international evidence for AD premia is striking; I show that AD is significantly priced in all stock markets examined. Among commonly considered factors, I find that asymmetric dependence is the only factor that is consistently priced in-sample across all markets considered. The coefficients attached to AD have a "Bayesianized" p-value (Harvey, 2017) lower than 1% in all of the countries analyzed with a t-statistics exceeding the Harvey, Liu, and Zhu (2014)'s value of 3.0. My findings are consistent with asymmetric dependence being a risk-based factor (see Griffin (2002)) that affects excess equity returns internationally.

I measure AD orthogonally to systematic and idiosyncratic risk. Accordingly, the AD premium is the reward investors expect for their acceptance of asymmetric dependence risk. Such risk is independent of the premium investors demand when they accept systematic and idiosyncratic risk (Alcock and Hatherley, 2016). My study controls for coskewness and cokurtosis to show that the AD risk premium is not confounded by any of these factors. I find that both lower- and upper-tail firm-level asymmetric dependence are important for international investors, who demand a premium for exposure to LTAD and accept a discount for the UTAD benefits.

In addition, the return premium required to hold stocks with lower-tail asymmetric dependence decreases, whereas the discount associated with upper-tail asymmetric dependence increases as the proportion of firms with returns exhibit-

[1] Lower- (upper-) tail asymmetric dependence describes a situation when a stock return correlation with market returns is higher during market downturns (upturns) relative to upturns (downturns), as illustrated in Figure 1.1.

ing lower-tail asymmetric dependence increases. In other words, a decrease in the 'supply' or the availability of AD makes it more valuable to investors, which is consistent with the general demand and supply for AD risk. My findings provide further evidence consistent with AD being a relevant risk-based factor that is associated with a non-negligible hedging cost.

I also contribute to a better understanding of the drivers of AD by empirically exploring the role macro-factors play in cross-country heterogeneity in the aggregated AD across countries. I explore whether economic risks (Ferson and Harvey, 1991), country-specific financial market risks (Erb, Harvey, and Viskanta, 1996), the law code origin (Porta, Lopez-de Silanes, Shleifer, and Vishny, 1998), or the World Bank Doing Business indicators that differ across countries can explain the country variations in AD by country.

I find that the degree of AD strengthens in countries experiencing faster growth in their financial markets. Similarly, the proportion of firms exhibiting LTAD increases as financial markets grow in size and importance. This has important implications for financial market stability, because growth in national market capitalization relative to GDP may be associated with negative effects for the real economy, ie potential abnormal losses experienced during market downturns.

These findings suggest that the financial markets considered in this study share common factors that influence the firm-level asymmetric dependence, as well as return sensitivity to AD. I find strong global and regional commonality effects in both the level and price of asymmetric dependence. The aggregate firm-level AD in different countries correlates with the global and regional aggregate AD levels. Country-specific investor sensitivity to AD is positively associated with the global and regional sensitivity to AD.

There is still disagreement in the existing literature about which factors explain the cross section of stock returns of international equities, despite the many studies exploring international factor pricing (Amihud, Hameed, Kang, and Zhang, 2015; Chan, Karolyi, and Stulz, 1992; Fama and French, 1998, 2012, 2017; Hou, Karolyi, and Kho, 2011; Lee, 2011; Van Dijk, 2011; Watanabe, Xu, Yao, and Yu, 2013). Furthermore, there is uncertainty as to whether only one set of risk factors impact asset prices in all countries, or the drivers are country-specific. My contribution to this debate provides evidence consistent with AD being a strong and consistent risk factor, that is priced in all markets considered.

This research builds on the previous work of Alcock and Hatherley (2016), who identify that US investors require additional compensation for assets with returns exhibiting lower-tail asymmetric dependence, and who accept a discount for holding stocks with upper-tail asymmetric dependence. Weigert (2015) shows that international investors require additional compensation as a form of protection against the risk of a market crash. In this paper, I argue that the entire continuum of asymmetric dependence between stock returns and market returns is relevant for investors in international markets, and that their preferences are not related to traditional consumption risk aversion. These results are consistent with international financial markets endowed with disappointment-averse investors (Skiadas, 1997).

This chapter is organised in the following sections. Section 3.1 describes my methods and Section 5.4 reports the data sample. Section 3.3 discusses the main results documenting the price of asymmetric dependence internationally, exploring the cross-country differences in the observed levels and prices of AD and studying the commonality effects of AD and AD pricing. Section 5.6 concludes.

3.1 Empirical Design

Estimating Risk Premia

I follow Alcock and Hatherley (2016) and Ang et al. (2006a) to provide evidence of the price of asymmetric dependence in each country individually. I examine the relation between asymmetric dependence and excess returns using the Ang et al. (2006a) cross-sectional regressions, while controlling for systematic risk, size, book-to-market ratio, momentum, idiosyncratic risk, coskewness, cokurtosis and illiquidity. I report the results for all the individual countries in the Appendix.

I consider and compare four main models with the following factors (regressors): Model (0) as log(size), book-to-market ratio, momentum, idiosyncratic risk, coskewness, cokurtosis, and illiquidity; Model (1) as: Model (0) and CAPM β, Model (2) as Model (1) and AD, Model (3) as Model (1) and LTAD and UTAD, and Model (4) as Model (0) and downside and upside β, and LTAD and UTAD.

At each month t, the average monthly excess return calculated using past twelve months of daily data is regressed against a subset of the following regressors: the J^{Adj}, CAPM β, upside and downside β, idiosyncratic risk, size, book-to-market ratio, Amihud (2002) illiquidity, coskewness, cokurtosis and the average of past 12 monthly excess returns estimated using daily returns from the past 12-month period (except for the illiquidity factor). The Amihud (2002) illiquidity factor is estimated using daily data from past 3 months. Regressors are winsorized at the 1% and 99% level each month to control for inefficient factor estimates. I use data on daily basis to ensure sufficient number of observations for the asymmetric dependence measure. The estimated values of the risk factors may be noisy relative to estimates based on lower frequency data, the significance tests should, however, have sufficient power since I use a relatively long data history (Lewellen and Nagel, 2006).

For a given month t, I calculate the J^{Adj}-statistic following Alcock and Hatherley (2016), using daily excess returns from the past 12 months with levels of exceedances: $\delta = \{0, 0.2, 0.4, 0.6, 0.8, 1\}$, which is also consistent with Hong, Tu, and Zhou (2007) and Alcock and Hatherley (2016).

The control variables from my regressions are calculated as follows. In a given month, t, the CAPM β, coskewness, cokurtosis are estimated using 12 months of past excess daily returns. Firm size is the log value of market value calculated over 12 months of past daily observations. The book-to-market ratio is the average BM from 12 months of past daily observations, where the book value of equity is the last end-of-year value observation. The idiosyncratic risk is measured as the standard deviation of CAPM residuals estimated using daily excess returns in past 12 months. Monthly excess returns are calculated from the continuously compounded excess daily returns. I use daily risk-free rate to obtain excess returns. The downside and upside β are defined as

$$\beta^- = \frac{\text{cov}(R_i, R_m | R_m < 0)}{\text{var}(R_m | R_m < 0)} \tag{3.1}$$

$$\beta^+ = \frac{\text{cov}(R_i, R_m | R_m > 0)}{\text{var}(R_m | R_m > 0)}, \tag{3.2}$$

where R_i is the excess return on asset i and R_m is the market excess return. I use the MSCI World Index as a market benchmark and the US one-month T-Bill rate as a proxy for a risk free rate to calculate excess returns.

I estimate the risk premia for each factor using cross-sectional regressions estimated every month rolling forward using a 12 month window. I use overlapping data in the monthly rolling-window estimations and therefore use the Newey and West (1987b) method to test for statistical significance and Newey and West (1994b) for automatic lag selection. I use a short-rolling window to identify the 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 asymmetric dependence risk (Alcock and Hatherley, 2016).

Country Panel Regressions

I explore the country variation in AD level and AD pricing. I first control for common factors affecting all countries. The commonality analysis is described in Section 3.1. I regress the residuals from commonality regressions that quantify the country-specific variation in AD and AD pricing, observed at the end of given year t on a list of regressors from Table 3.6 in the Appendix. I use the residuals from equations (3.3) and (3.4) instead of country levels and prices of AD to control for regional and global common factors.

I use data from 2004 until 2015, because the Doing Business Indicators issued by the World Bank are not available before 2004. If return data is not yet available for a given stock exchange in 2004 in the WRDS Compustat Global dataset, I use the maximum available data window fort this given financial market.

I analyze the country variation in AD using panel regressions with and without fixed-year effects and cluster standard errors by countries. I apply first differencing to all the variables from Table 3.6, except the dummy variables describing short selling practices and law code. First differencing helps in reducing the impact of collinearity (the Variance Inflation Factor reduced to less than 10 for all variables in the model).

Commonality Effects

I divide the countries into three regions consistent with Amihud et al. (2015). My sample covers 6 countries from Americas (Argentina, Canada, Chile, Mexico, Peru and US), 11 Asian-Pacific countries (Australia, China, Hong Kong, India, Indonesia, Japan, Korea, New Zealand, Pakistan, Philippines and Singapore) and 20 European (or closely related to Europe) countries (Austria, Belgium, Denmark, Egypt, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Poland, Romania, South Africa, Spain, Sweden, Switzerland, Turkey and UK).

I analyze how country levels of AD and return sensitivity to AD are linked with its global and regional values.[1] I start by exploring the commonalities in the level of AD and regress the mean country level of J^{Adj} (across all firms from country c) at month t (J^{Adj}_{ct}) on global and regional levels of AD at month t (J^{Adj}_{gt} and J^{Adj}_{rt}), while controlling for the monthly market excess returns (r_{mt}), see regression model in (3.3).[2]

$$J^{Adj}_{ct} = \alpha_{0c} + \alpha_{1c} J^{Adj}_{gt} + \alpha_{2c} J^{Adj}_{rt} + \alpha_{3c} r_{mt} + \epsilon_{ct}. \tag{3.3}$$

A commonality in the level of AD is indicated by a positive and significant coefficient α_{1c} and/or α_{2c}. The global level of asymmetric dependence (J^{Adj}_{gt}) is the weighted average value of the J^{Adj} across all the countries from my sample, and the regional level of asymmetric dependence (J^{Adj}_{rt}) is the weighted average value of the J^{Adj} across all the countries from a given region. ϵ_{ct} represents regression residuals. Weights assigned to each financial market are based on the number of distinct firms listed on a given stock exchange.

Next, I analyze the commonalities in the variations of return premia attached

[1] The subscripts c, g and r represent the country, global and regional values of AD and sensitivity to AD in all the regressions in this section.

[2] J^{Adj}_{rt} is orthogonalized to J^{Adj}_{gt}. I regress J^{Adj}_{rt} on J^{Adj}_{gt} and use the residual and intercept, excluding the global effect on regional value, as the regional factor. I exclude country c when calculating the global and regional values.

to AD, see the model described from (3.4). I regress the mean return premium attached to the J^{Adj} in country c at month t (γ_{ct}) on a global level of return premium attached to the J^{Adj} in month t (γ_{gt}), calculated as a weighted average of return premium from month t across all countries from the sample, regional level of return premium attached to the J^{Adj} in month t (γ_{rt}), calculated as a weighted average of return premium from month t across all countries from a given region (Americas, Europe, or Asia-Pacific), the global level of AD (J^{Adj}_{gt}) and regional level of AD (J^{Adj}_{rt}). The regional values of the level of AD (J^{Adj}_{rt}) and sensitivity to AD (γ_{rt}) are orthogonalized to its global counterparts (J^{Adj}_{gt} and γ_{gt}). ξ_{ct} are regression residuals.

$$\gamma_{ct} = \delta_{0c} + \delta_{1c}\gamma_{gt} + \delta_{2c}\gamma_{rt} + \delta_{3c}J^{Adj}_{gt} + \delta_{4c}J^{Adj}_{rt} + \xi_{ct} \tag{3.4}$$

3.2 Data

I explore the price of asymmetric dependence (AD) on a sample of 38 stock exchanges. I select the largest stock exchange in each country except for China, where I analyze both the Shanghai and Shenzhen stock exchange. I include both stock exchanges from China (Shanghai and Shenzhen) and decide not to pool them together due to differing listing requirements. I have data on 31,893 individual firms from the 38 stock exchanges and 3,506,776 firm-month observations. Table 3.1 describes the sample period, the number of distinct firms and firm-month observations for all the financial markets considered.

For each country except the US, I retrieve daily stock price information from WRDS Compustat Global Security Daily database (G_SECD). I obtain a time series of daily firm identifier (gvkey), date, close price (prccd), daily cash dividend

Data Description

Table 3.1: This tables describes the data used from country i, including the sample period, number of distinct firm and number of firm-month observations. I record data from December 31, 1985 when the market proxy (MSCI World Index) becomes available in the WRDS Database.

Country i	Sample Period (dd/mm/yyyy)	Distinct Firms	Firm-Month Observations
Argentina	03/01/89 - 31/12/2015	89	10,333
Australia	02/01/87 - 31/12/2015	2,446	206,232
Austria	04/01/88 - 31/12/2015	147	13,884
Belgium	02/01/87 - 31/12/2015	211	24,392
Canada	31/12/85 - 31/12/2015	837	48,616
Chile	01/06/92 - 31/12/2015	223	18,050
China (Shanghai)	15/02/94 - 31/12/2015	934	124,378
China (Shenzhen)	15/02/94 - 31/12/2015	1,545	122,054
Denmark	02/01/87 - 31/12/2015	281	28,280
Egypt	06/01/97 - 31/12/2015	192	12,372
Finland	02/01/87 - 31/12/2015	177	23,391
France	02/01/87 - 31/12/2015	1,185	124,608
Germany	02/01/87 - 31/12/2015	900	87,963
Greece	01/06/92 - 31/12/2015	296	34,364
Hong Kong	02/01/87 - 31/12/2015	1,640	179,731
India	02/01/90 - 31/12/2015	2,065	88,646
Indonesia	30/05/90 - 31/12/2015	519	46,726
Ireland	31/05/95 - 31/12/2015	519	45,046
Italy	02/01/87 - 31/12/2015	457	52,001
Japan	02/01/87 - 31/12/2015	3,432	690,034
Korea	05/01/87 - 31/12/2015	1,855	231,945
Mexico	02/01/91 - 31/12/2015	155	14,406
Netherlands	02/01/87 - 31/12/2015	271	32,772
New Zealand	05/01/87 - 31/12/2015	171	16,429
Norway	02/01/87 - 31/12/2015	319	28,118
Pakistan	03/01/94 - 31/12/2015	418	33,645
Peru	16/08/94 - 31/12/2015	104	8,510
Philippines	03/01/89 - 31/12/2015	265	26,068
Poland	10/08/95 - 31/12/2015	636	43,786
Portugal	03/01/89 - 31/12/2015	94	9,334
Romania	19/05/98 - 31/12/2015	76	4,578
Singapore	02/01/87 - 31/12/2015	946	96,766
South Africa	01/06/92 - 31/12/2015	487	45,904
Spain	05/01/87 - 31/12/2015	492	46,815
Sweden	02/01/87 - 31/12/2015	628	57,325
Switzerland	05/01/87 - 31/12/2015	296	42,656
Turkey	13/02/90 - 31/12/2015	403	39,413
UK	02/01/87 - 31/12/2015	3,447	309,433
US	31/12/85 - 31/12/2015	2,880	437,772
Total		31,983	3,506,776

amount (div), daily volume (cshtrd) and number of shares outstanding (cshoc). I collect annual balance sheet information from WRDS Compustat Global Fundamentals Annual database. I collect firm identifier (gvkey), financial year (fyear), common equity (ceq) for all listed equities. Data is collected in US dollars. I select only common equity, where "TPCI - Issue Type Code" from the Compustat Global Security Daily database is equal to 0 (Common, ordinary shares).

US data is collected from CRSP Security Daily database. I include only common shares (CRSP share code 10 or 11). I obtain CRSP return (ret), close price (prc), number of shares outstanding (shrout), daily volume (vol) and use permno as the main firm identifier. I use listings with the NYSE main stock exchange only (where "hexcd=1") to avoid potential biases due to cross listings or different listing requirements. I collect end-of-year information about the firm common equity values (ceq) from the Compustat Fundamentals Annual database.

For all countries, except the US, I calculate total return as the sum of the capital gain and yield on dividends: $R_{it} = \frac{P_t - P_{t-1} + D_t}{P_{t-1}}$, where P_t and P_{t-1} are close prices from day t and the previous day $t-1$ and D_t is the cash amount of dividends paid out on day t. For US equities, I use the CRSP return, which already incorporates both capital gains as well as dividend income.

I use the MSCI World Index as the market proxy and the US one-month T-Bill rate collected from WRDS Fama French Factors dataset for the proxy of risk free rate in all countries examined. This approach is consistent with existing international asset-pricing studies (Amihud et al., 2015; Karolyi et al., 2012).

I follow Ince and Porter (2006) and set any daily return R_{it} of firm i on day t to zero if r_{it} exceeds 200% or if $R_{it} > 100\%$ and $(1+R_{it}) \times (1+R_{it-1}) - 1 < 20\%$. I use this procedure to screed for data errors indicating substantial returns that are reversed within one month. Furthermore, I exclude all daily returns with negative

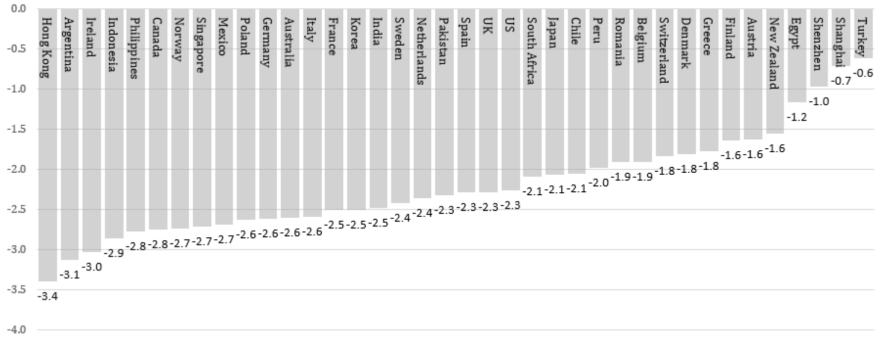
BM to cover for potential data errors. I apply a liquidity rule and remove stock-return time series with more than 50% of zero or missing daily returns. For each month t, only stock return time series with data available in months $t-12$ to $t+12$ are included in the final data set. I only consider such stock exchanges that have at least 50 listed firms and start analyzing the return time-series of such financial exchanges only after the number of firms exceeds 50.

Descriptive Statistics

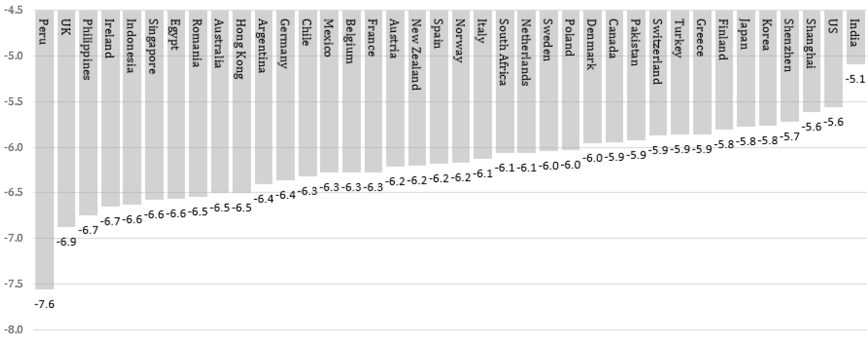
The country mean level of J^{Adj} ranges from -0.617 (Turkey) to -3.395 (Hong Kong), Figure 3.1. A negative mean J^{Adj} observed across all countries suggests that there are more firms exhibiting LTAD ($J^{Adj} < 0$) than UTAD ($J^{Adj} > 0$) in all of the world largest stock exchanges, given that the magnitude of the firm-level LTAD and UTAD is comparable in the stock markets considered, see Table 3.1 in the Appendix. The relatively low absolute value of the mean J^{Adj} in the Turkey can be explained by a lower number of firms exhibiting LTAD returns relative to other countries. The highest degree of both LTAD and UTAD is recorded in Peru, which suggests that firms in Peru exhibit highly asymmetric tail correlations.

The values of mean βs range from low 0.191 (Shanghai) to high 1.050 (Turkey). The relatively low observed values of the CAPM β may be attributed to the usage of noisy daily data, which may result in a low correlation with the market proxy (Vasicek, 1973) and/or the choice of the global market proxy (MSCI World index). The main results remain qualitatively similar when local market proxies are used. Table 3.7 describes summary statistics of the factor of the main interest, the firm-level asymmetric dependence (J^{Adj}), as well as of all the control variables used in my pricing regressions: CAPM β, log-size, BM, past returns, idiosyncratic risk, coskewness, cokurtosis and illiquidity.

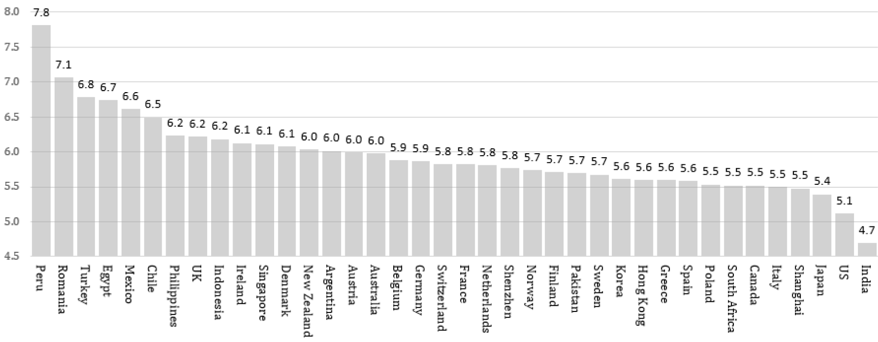
The Degree of Asymmetric Dependence: Country Comparison



(a) Asymmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 3.1: This figure shows the country levels of asymmetric dependence (3.1(a)), lower-tail asymmetric dependence (3.1(b)) and upper-tail asymmetric dependence (3.1(c)), respectively. The country level of asymmetric dependence corresponds to the equally-weighted average value of firm-specific asymmetric dependence (measured using J^{Adj}) across all firms listed in a given financial market. The description of data used is provided in Table 3.1.

The J^{Adj} is largely uncorrelated with other risk factors (Table 4.2 in the Appendix), except coskewness. The J^{Adj} captures higher-order dependence structure and therefore also contains information about the third co-moment. The J^{Adj} is constructed to describe and combine information from all the higher-order asymmetries in return correlations, that may be attributed to any of the higher-order co-moment, and shall not, therefore, be considered as just another (different) measure of the third co-moment. In order to justify the relevance of the J^{Adj} for the variations in the cross section of equity returns, I also include coskewness and cokurtosis in the pricing regressions as control variables.

3.3 Results

The International Pricing of Asymmetric Dependence

The firm level asymmetric dependence (J^{Adj}) is significantly priced in all in-sample regressions, and all out-of-sample pricing regressions except Egypt and Mexico. I use the Fama and MacBeth (1973) asset-pricing procedure to estimate the out-of-sample regressions and the Ang and Chen (2002)'s method to conduct the in-sample tests. In all of the countries in my study, the coefficient associated with the degree of the firm-level asymmetric dependence is positive. This result is ubiquitous and strongly consistent with the view that asymmetric dependence between stock returns and market returns is a general risk-based factor, rather than being an anomalous characteristic of the US market.

The value-weighted average t-statistic associated with the firm-level asymmetric dependence is 5.876. See Model (2) from Table 3.2.[1] In 34 out of 38 markets, the t-statistic is greater than the Harvey, Liu, and Zhu (2014) hurdle rate of 3.0,

[1] I use the number of listed equities in each stock market as weights to calculate the average regression coefficients and t-statistic from Table 3.2.

Main Results: Summary

Table 3.2: This table shows the mean country-level cross-sectional regression coefficient and mean t-statistics (in parenthesis, in absolute values) estimated using Fama and MacBeth (1973) reressions. The stock exchange size (the number of listed companies from Table 3.1) is used as a weight to calculate the value-weighted average coefficient and t-statistics. This table summarizes the risk premia measured using the Ang et al. (2006a) asset-pricing procedure where equally-weighted cross-sectional regressions are computed every month rolling forward. The detailed country-specific results are available in the Appendix. The coefficients are calculated for each country individually as follows. At a given month, t, the average excess monthly return calculated using the past twelve months of daily data is regressed against AD (J^{Adj}), LTAD ($J^{Adj}-$), UTAD ($J^{Adj}+$), β, size ("Log-size"), book-to-market ratio ("BM"), the average past 12-monthly excess return ("Past Ret"), idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and illiquidity factor ("Illiq"). The book-to-market ratio ("BM") at time t for a given stock is computed using the last available (most recent) book equity entry. The Amihud (2002) illiquidity factor ("illiq") at month t is estimated using daily data from $t-3$ until t. Statistical significance is determined using Newey and West (1987b) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994b) automatic lag selection method to determine the lag length. All coefficients are reported as effective annual rates. Risk premia are estimated using all data available, a description of the data sample is provided in Table 3.1. MSCI World index and the US 1-month T-Bill rate are used as a market and risk free rate proxy. All returns are in US dollars.

	Model (1)		Model (2)		Model (3)		Model (4)	
Intercept	-0.041	[0.186]	-0.133	[0.486]	-0.160	[0.586]	-0.120	[0.498]
β	-0.050	[1.372]	-0.071	[1.246]	-0.074	[1.274]		
Log-size	0.001	[0.075]	0.003	[0.238]	0.003	[0.287]	0.003	[0.314]
BM	0.015	[2.130]	0.016	[1.576]	0.016	[1.556]	0.015	[1.869]
Past Ret	-1.147	[4.409]	-1.084	[2.750]	-1.076	[2.671]	-1.084	[3.974]
Idio	5.002	[2.933]	4.999	[1.779]	5.038	[1.736]	4.023	[2.415]
Cosk	-0.045	[0.629]	0.158	[1.773]	0.146	[1.638]	0.584	[4.053]
Cokurt	-0.004	[0.164]	0.026	[0.691]	0.029	[0.785]	0.006	[0.211]
Illiq	-0.654	[0.038]	-0.590	[1.123]	-0.637	[1.398]	-0.616	[0.648]
β^-							0.034	[2.255]
β^+							-0.039	[2.494]
AD			-0.014	[3.153]				
LTAD					-0.015	[2.965]	-0.015	[4.485]
UTAD					-0.012	[2.536]	-0.013	[3.689]

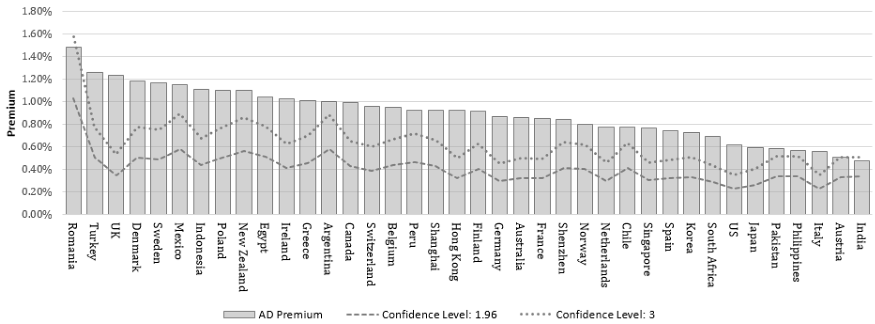
set to account for data mining issues and noise in variables. In all the countries sampled, the coefficient associated with the J^{Adj} is positive, see Figure 3.2. The positive sign projects that the higher the degree of AD, the higher the expected excess return in one month. This further supports the Skiadas (1997) disappointment theory, where investors expect additional compensation in return for asymmetric dependence risk. Table 3.2 summarizes my main results, while country-specific details are described in Appendix A.

My findings add further to our understanding of the risk-return drivers of international asset prices of listed equities. I find that the mean coefficient associated with CAPM β is negative and insignificant. The coefficient attached to the CAPM β is either insignificant or negative. My findings are consistent with a large number of studies documenting a negative (or insignificant) price of CAPM β risk (Daniel and Titman, 1997; Hou et al., 2011; Weigert, 2015; Zhang, 2006). I do not find any out of sample evidence that systematic risk, as measured using the CAPM β or upside and downside βs, is relevant for international investors, whereas AD is.

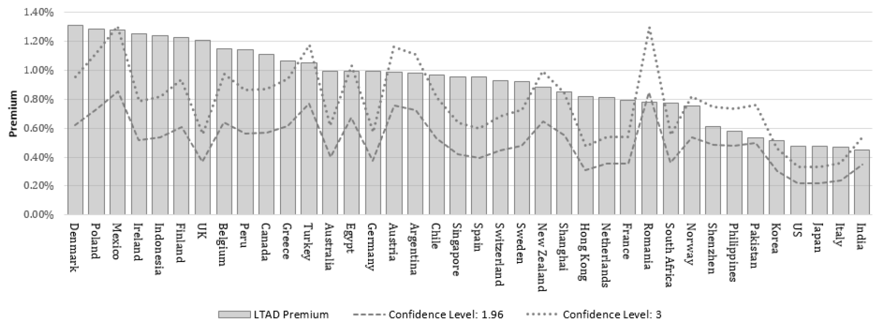
The existence of AD and AD pricing has important implications for risk-based investment strategies that determine capital allocation, based on the bivariate distribution of firm returns and market returns. In the 38 largest financial markets, asymmetric characteristics of return correlations are relevant for international investors with state-dependent preferences (see Skiadas (1997)), as they may value potential gains and losses unevenly. Indeed, I suggest that the entire continuum of asymmetric dependence is highly relevant for international investors.

My results of AD pricing are not confounded by the effect of systematic or idiosyncratic risk. I use a measure of the firm-level AD (J^{Adj}) that is orthogonal to firm-level CAPM β and idiosyncratic risk. This is an important distinction from other studies that use copulae techniques to measure tail dependence. For

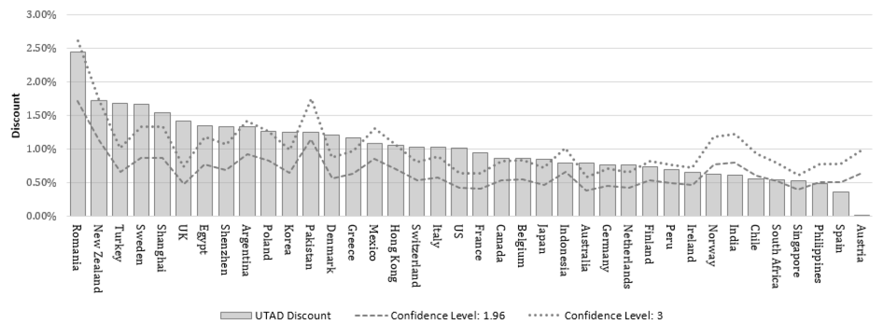
The Price of Asymmetric Dependence: Country Comparison



(a) Asymmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 3.2: This figure shows the country price of asymmetric dependence (3.2(a)), lower-tail asymmetric dependence (3.2(b)) and upper-tail asymmetric dependence (3.2(c)), respectively. The significance of the price of asymmetric dependence (J^{Adj}) is measured using the in-sample Ang et al. (2006a) asset-pricing procedure where equally-weighted cross-sectional regressions are computed every month rolling forward. At a given month, t, the one-month excess monthly return from t is regressed against J^{Adj} (or $J^{Adj}-$ and $J^{Adj}+$, respectively), β, size ("Log-size"), book-to-market ratio ("BM"), the average past 12-monthly excess return ("Past Ret"), idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and illiquidity factor ("Illiq"). The description of data used is provided in Table 3.1. The dashed line represents the confidence interval associated with the t-statistic of 1.96 (5% confidence level) and the dotted line is associated with the confidence interval related to a t-statistic of 3.0 (the Harvey et al. (2014) hurdle rate for t-statistic).

example, see Low, Alcock, Faff, and Brailsford (2013); Oh and Patton (2017); Patton (2012); Weigert (2015) or Genest, Gendron, and Bourdeau-Brien (2009).

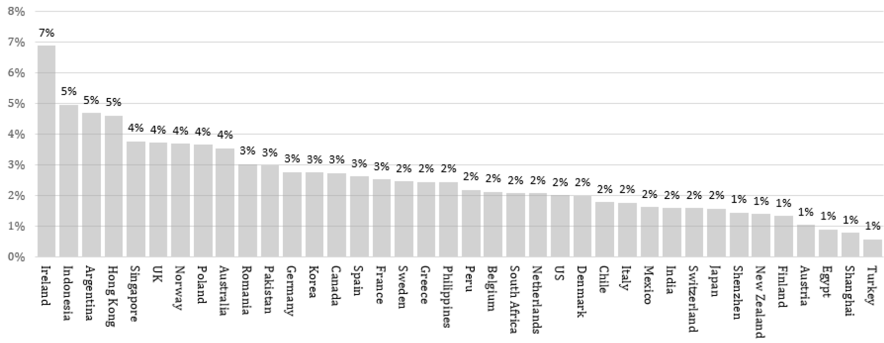
International asset-pricing studies provide one of few tools to assess whether a priced firm-level characteristics is a risk-based factor or a data-mining-related anomaly (Griffin, 2002). Using different data samples from different financial markets to replicate the estimation of the AD risk premium 38 times, I find that AD pricing is ubiquitous. Again, this is consistent with AD being a risk-based factor relevant for investors internationally.

I estimate that the 'typical' return premium attached to AD[1] expected by investors ranges from a low 1% per annum (Turkey) to a high 7% per annum (Ireland), Figure 3.3. Investors most sensitive to AD are those in Ireland, Indonesia, Argentina and Hong Kong, all of whom require a 'typical' return premium of more than 5% per annum for holding a stock with an average degree of AD.

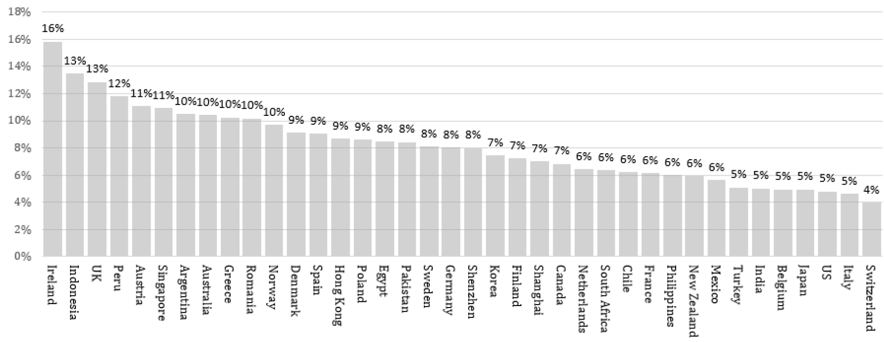
The pricing evidence of other commonly considered factors remains largely consistent with existing literature. BM ratio is positively priced in 17 out of 38 markets. The positive coefficient associated with the BM ratio is consistent with the Fama and French (1992, 1998, 2012, 2017) and Amihud et al. (2015)'s findings. The Amihud (2002) illiquidity factor is significant only in the US and Singapore, which contrasts with Amihud, Hameed, Kang, and Zhang (2015) findings. I exclude highly illiquid firm observations from the sample (see exclusion rules described in Section 5.4), which may explain why the significance of the illiquidity premia is lower in my results than in Amihud et al. (2015).

[1] The 'typical' price of AD is defined as the product of the mean J^{Adj} and the estimated regression coefficient associated with J^{Adj}.

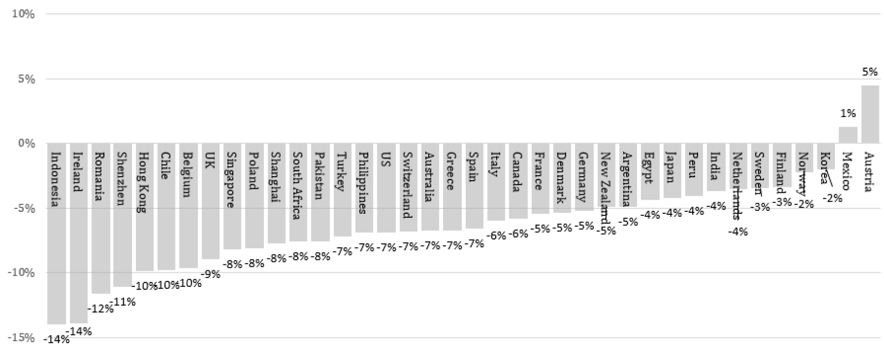
The “Typical Price” of Asymmetric Dependence: Country Comparison



(a) Asymmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 3.3: This figure shows the typical price of asymmetric dependence (3.3(a)), lower-tail asymmetric dependence (3.3(b)) and upper-tail asymmetric dependence (3.3(c)), respectively. The typical price of AD is defined as the product of the mean J^{Adj} and the estimated regression coefficient associated with J^{Adj}. The description of data used is provided in Table 3.1.

Lower-tail and Upper-tail Asymmetric Dependence

I explore the pricing of two notably distinct types of asymmetric dependence, lower-tail asymmetric dependence (LTAD) and upper-tail asymmetric dependence (UTAD). I quantify the price of the two types of AD, LTAD ($J^{Adj}-$) and UTAD ($J^{Adj}+$), separately, by including them as risk factors in the out-of-sample pricing regressions, Model (3) from Table 3.2. I find that at least one of the two factors, LTAD or UTAD, is significant in all the countries, except for Mexico, Romania and Turkey.[1]

Out of sample, in almost all the markets, LTAD (UTAD) is associated with positive (negative) and significant coefficients. This is consistent with my hypothesis as the positive coefficient implies that the higher the degree of LTAD (measured using $J^{Adj}-$), the higher the excess return in next month, suggesting a **return premium** required by investors to bear **lower-tail asymmetric dependence** risk.[2] The negative coefficient suggests that the higher the degree of UTAD (measured using $J^{Adj}+$), the lower the excess return in the following month, which indicates a **return discount** attached to **upper-tail asymmetric dependence**.

Significantly, I must be able to distinguish between these two types of AD, since they have opposite implications for expected returns (premium or discount). This is of critical importance for investor. I explain my empirical results in the context of the Skiadas (1997) disappointment theory. Stock returns exhibiting LTAD (UTAD) are associated with a return premium (discount) because investors with state-dependent preferences may feel disappointed (elated) for having to hold an LTAD (UTAD) asset relative to a symmetric asset. Having access to information

[1] For details on all country-level regressions, please refer to Tables from Appendix A.

[2] I note that $J^{Adj}-$ is always negative and when returns are regressed on $J^{Adj}-$, the coefficient associated with $J^{Adj}-$ is negative. I choose to report a positive regression coefficient to be consistent with a common convention that positive coefficient suggests a return premium and a negative regression coefficient indicates a return discount.

about the current type and degree of AD is clearly important for the international investor.

In terms of whether investors are concerned about upside and downside βs, I add further clarification by adding the upside β (β^+) and downside β (β^-) into the pricing regressions, see Model (4) from Table 3.2. I find that investors value LTAD and UTAD, as measured by $J^{Adj}-$ and $J^{Adj}+$, respectively, more than they value upside and downside βs.

The 'typical' return premium (discount) associated with LTAD (UTAD), estimated using the in-sample regressions, range from 1% to 16% (2% to 14%), Figure 3.3. The 'typical' price of LTAD (UTAD) corresponds to the size of the premium (discount) required to hold a stock with an average degree of LTAD (UTAD). In Ireland, I find that investors are most sensitive to both LTAD and UTAD, having the highest price per unit of $J^{Adj}-$ and $J^{Adj}+$ recorded, Figures 3.2b) and 3.2c). The cross-sectional return sensitivity to one unit of LTAD (UTAD) ranges between 0.68% to 2.38% (-0.75% to 2.26%) across countries. The price of LTAD and UTAD is consistent across the sample. The coefficient associated with LTAD is positive in all countries examined. The sign of the coefficient attached to UTAD is negative in all sample countries, except for Mexico and Austria.

I test for the equality of the risk premia attached to AD that is observed across countries and find that in 61.35% of country pair combinations, I can can reject the null hypothesis of equal AD premia (at 5% level). These results suggest that investors in some countries care differently about the same unit level of AD, which may be possibly linked to the cost and options for downside insurance product, which may vary across countries.

Drivers of Asymmetric Dependence

I study the sources of country variations in the degree of firm-level asymmetric dependence and AD premia among countries. Our research is informed by existing literature (Ferson and Harvey, 1991, 1994) that explores the effects of economic risks on common factors.

I examine the relation between the observed degree and price of asymmetric dependence and a number of country characteristics. In particular, I analyze the role of economic risks, country-specific financial market risks, short selling restrictions, the law code origin, conditions to do business and other country-specific characteristics in explaining the variations in AD among countries (Beck et al., 2003; Djankov et al., 2002, 2003, 2007, 2008; Erb et al., 1996).

I find that the change in the market capitalization to GDP, turnover, law origin and the change in country conditions to start a business are useful in identifying the differences in the changes in the degree of asymmetric dependence or return sensitivity to AD among countries, Table 3.3.

Market Capitalization to GDP

I find that a change in the market capitalization to GDP ratio (Δ MCAP to GDP) is related with a decrease in the change in the level of asymmetric dependence, Table 3.3. This effect of Δ MCAP to GDP on changes in the degree of AD may come from an increase in the degree of LTAD, a decrease in the degree of UTAD, or an increase in the proportion of firms with LTAD returns, because the aggregate degree of AD is calculated as a weighted average of the firm-level LTAD and firm-level UTAD.

I investigate the sources of the effect of Δ MCAP to GDP on the degree of asymmetric dependence and find that it comes primarily from changes in the

Panel Regressions: Country-level Drivers

Table 3.3: This table reports panel regression estimation results. The first difference of country level of AD residuals (Model (1)), $\Delta\epsilon_{ct}$ from the model described in equation (3.3)), the first difference of country return premium attached to AD (Model (2)), $\Delta\xi_{ct}$ from the model described in equation (3.4)), and the proportion of LTAD firms (Model (3)) observed at the end of year t are regressed on a list of country characteristics from Table 3.6 measured at the end of year t. All regressors (except for Short Practiced, and Law Code dummies) are differenced. The sample is limited to years 2004-2015, because World Bank Doing Business Indicators are not available before 2004. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Table also reports whether year effects are used in the regression (Yes/No), number of observations and the adjusted R-squared coefficient. The regression results are robust to the choice of the Law Code dummy variable base (English Law Code in this regression).

	(1) Δ Level of AD ($\Delta\epsilon_{ct}$)	(2) Δ AD Premium ($\Delta\xi_{ct}$)	(3) Δ Prop. of LTAD
Δ Starting a Business (DTF)	0.0432	-0.000094	-0.00634***
	(0.0460)	(0.0002)	(0.0022)
Δ Getting Credit (DTF)	0.0159	0.000145	0.00102
	(0.0351)	(0.0001)	(0.0020)
Δ Protecting Investors (DTF)	0.0324	-0.0000608	0.00114
	(0.0476)	(0.0001)	(0.0018)
Δ Enforcing Contracts (DTF)	-0.0199	-0.000126	-0.00385
	(0.0500)	(0.0004)	(0.0030)
Δ Resolving Insolvency (DTF)	0.0198	0.000354***	-0.00235
	(0.0236)	(0.0001)	(0.0014)
Δ Paying Taxes (DTF)	-0.0493	-0.000306	0.00133
	(0.0420)	(0.0002)	(0.0031)
Δ Trading Across Borders (DTF)	-0.0636**	0.000175	-0.000439
	(0.0290)	(0.0002)	(0.0020)
Short Practiced	0.116	0.00015	-0.0158
	(0.1230)	(0.0007)	(0.0094)
French Law	0.203	0.000647	0.00518
	(0.1560)	(0.0007)	(0.0100)
German Law	0.0379	0.000211	0.0233*
	(0.2060)	(0.0011)	(0.0132)
Scandinavian Law	0.143	0.00106	0.00955
	(0.1110)	(0.0006)	(0.0073)
Δ Inflation	-0.0429	0.000262	-0.00195
	(0.1230)	(0.0006)	(0.0067)
Δ Turnover	0.00365	0.0000388	-0.000305
	(0.0043)	(0.0000)	(0.0002)
Δ MCAP	-0.00548***	-1.91e-05**	0.000167***
	(0.0010)	(0.0000)	(0.0001)
Δ Log(Population)	-9.858	0.0626	1.660**
	(12.5)	(0.1)	(0.7)
Δ Log(GNI)	3.82	-0.0283	-0.491**
	(4.3)	(0.0)	(0.2)
Constant	0.128	0.00287	0.0979***
	(0.6850)	(0.0026)	(0.0296)
Year Effects	Yes	Yes	Yes
Observations	225	225	225
R-squared	0.818	0.151	0.889

proportion of LTAD firms. Indeed, in countries with increasing values of MCAP to GDP, the proportion of firms exhibiting LTAD increases relatively more.

My findings suggest that in countries where the relative importance of the financial markets increases, i.e. in countries with increasing Δ MCAP to GDP, the overall effect of asymmetric dependence on asset prices and the real economy becomes pronounced. This is because in these fast-growing financial markets, the number of firms exhibiting LTAD increases and the effects of financial crises may thus become more severe.

Moreover, I find that the proportion of firms with stock returns exhibiting LTAD correlates with country-specific conditions to start a business. When conditions to start a business improve at a faster rate, i.e. the change in the distance to frontier (DTF)[1] decreases, the change in the proportion of firms with LTAD returns increases. I notice that the conditions required to start a business has a similar effect on the proportion of LTAD firms as the relative importance of financial markets in the economy, i.e. the ratio of MCAP to GDP. As a result, these findings suggest that when more firms are created and financial markets grow relative to GDP, the proportion of LTAD firms increases.

My findings signal an important message for regulators and policy makers. I provide evidence that a fast growth of financial markets may not always be associated with positive effects to the economy. In fact, I find that as the financial market growth increases, the proportion of LTAD firms increases and investors become more sensitive to asymmetric dependence. This adds further support for the recognition of the firm level of asymmetric dependence as a relevant risk factor.

[1]The Doing Business Distance to Frontier score (DTF) shows the distance of an economy to the "frontier", which is derived from the most efficient practice or highest score achieved on each indicator.

Country Characteristics: Correlation Matrix

Table 3.4: Pair-wise correlations of regressors used in Panel Regressions from Table 3.3. Regressors are described in Table 3.6.

	Δ Start. Business	Δ Get. Cred.	Δ Prot. Inv.	Δ Enfor. Con.	Δ Resol. Insolv.	Δ Pay. Tax.	Δ Trad.	Δ Infl.	Δ Turn.	Δ MCAP	Δ Pop.
Δ Get. Cred.	0.150										
Δ Prot. Inv.	0.090	-0.150									
Δ Enfor. Con.	0.010	0.220	0.140								
Δ Resol. Insolv.	-0.050	-0.010	0.080	0.040							
Δ Pay. Tax.	0.020	0.080	0.000	0.050	0.100						
Δ Trad.	0.110	0.000	0.250	0.000	0.020	0.100					
Δ Infl.	0.100	0.100	-0.030	0.030	0.060	-0.100	0.120				
Δ Turn.	-0.010	-0.020	0.000	0.060	0.100	-0.110	0.060	0.350			
Δ MCAP	0.010	0.020	0.040	-0.020	-0.020	0.000	0.080	-0.270	-0.250		
Δ Pop.	-0.030	0.080	-0.120	-0.040	-0.040	0.000	-0.170	0.070	-0.030	-0.040	
Δ GNI	0.190	0.070	0.030	0.090	0.040	-0.040	0.000	0.280	0.120	-0.010	0.310

Time Variations of Asymmetric Dependence

I explore co-movements of the time-series variations in the country aggregate levels of AD and AD pricing in the global as well regional context. From 2000 to 2015, the global[1] level of asymmetric dependence was relatively volatile. The changes in the overall global level of AD are mainly driven by changes in the proportion of LTAD and UTAD firms in the markets, rather than changes in the degree of AD. The levels of LTAD and UTAD remain relatively stable and fluctuate around values -6 and 6, respectively.

The proportion of firms with returns exhibiting LTAD changes considerably, ranging between 30% to 95%, as illustrated by the shaded area in Figure 3.4. With a high proportion of LTAD firms, the global aggregated firm-level AD (which is a weighted average of the firm-level LTAD and UTAD, is driven mainly by LTAD (i.e. $J^{Adj} < 0$), and therefore becomes more negative. This explains the significant decline in the global level of AD during 2013 and 2014 when the proportion of LTAD increased considerably.

The regional levels of AD, LTAD as well as UTAD are strongly correlated across regions, Figure 3.5. Despite similarities in levels of AD across the three regions, the degree of LTAD in Europe is relatively higher compared to the other two regions in the period 2010 to 2014.

I observe a negative (positive) correlation of 52.66% (-15.20%) between the return premium (discount) attached to LTAD (UTAD) and the proportion of firm returns exhibiting LTAD. The relationship between the price of LTAD (UTAD) and the proportion of firm returns exhibiting LTAD is statistically significant with a t-statistics of 1.96 (8.31, respectively), measured by regressing the global price

[1]The term "global" refers to the value-weighted average across all countries considered. The term "regional" refers to the value-weighted average across all countries from a given region (Americas, Asian-Pacific or Europe). Stock exchange size (number of listed companies) is used as weights.

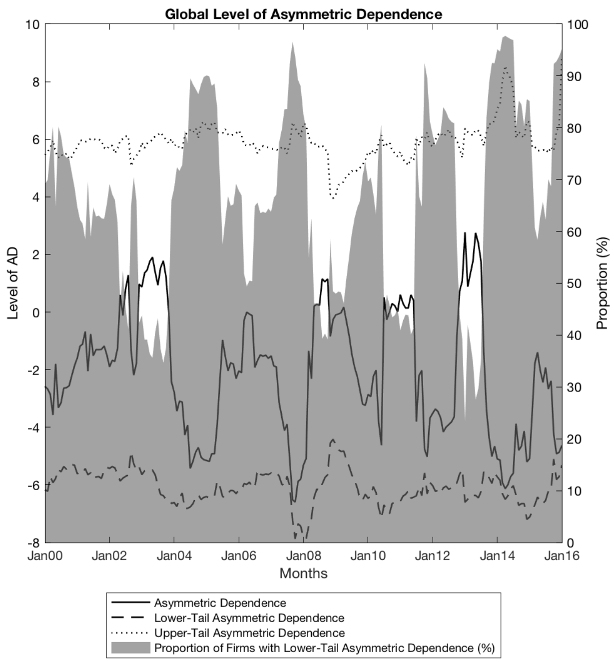
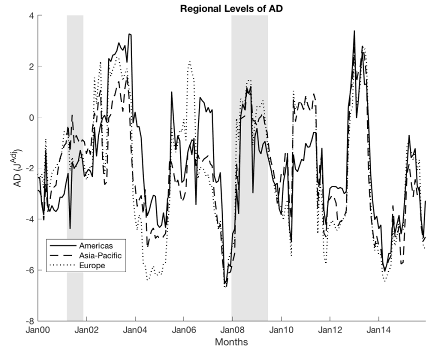
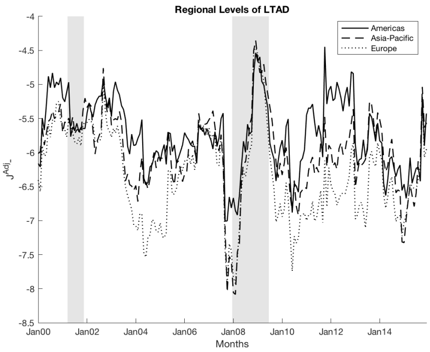


Figure 3.4: Time series of the “global” level of asymmetric dependence, lower-tail asymmetric dependence and upper-tail asymmetric dependence. The “global” of asymmetric dependence in month t is calculated as a weighted average of country levels of asymmetric dependence from month t. Shaded areas represent the weighted average of country proportion of LTAD firms (relative to UTAD firms). The “global” level of AD refers to a value-weighted average of country-specific AD in time t, where weights reflect the size of country’s stock exchange (measured using the number of distinct firms listed in each stock exchange).

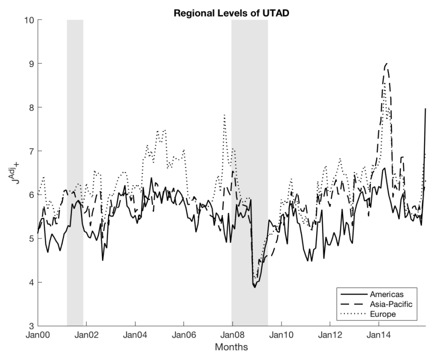
Regional Levels of AD



(a) Asymmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 3.5: Time series of the "regional" level of asymmetric dependence (Panel (a)), lower-tail asymmetric dependence (Panel (b)) and upper-tail asymmetric dependence (Panel (c)). The "regional" level of asymmetric dependence in month t is calculated as a weighted average of country levels of asymmetric dependence from month t for all countries within a region (Americas, Asia-Pacific and Europe). Country weights used to calculate weighted averages reflect the size of country's stock exchange (measured using the number of distinct firms listed in each stock exchange). Shaded areas represent NBER crisis periods.

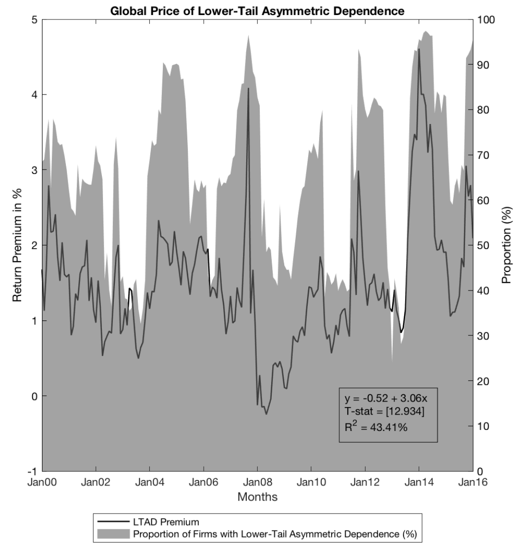
of LTAD (UTAD) on the value-weighted proportion of firms with LTAD returns observed at month t.

These findings are consistent with a general demand and supply model, where investors assign a higher price to a firm characteristic that is relatively more scarce in the market. These findings imply that with a higher proportion of firms exhibiting LTAD, the LTAD (UTAD) premium is relatively lower (higher). As a result, the price of LTAD is negatively associated with UTAD having a correlation coefficient of -41.72%.

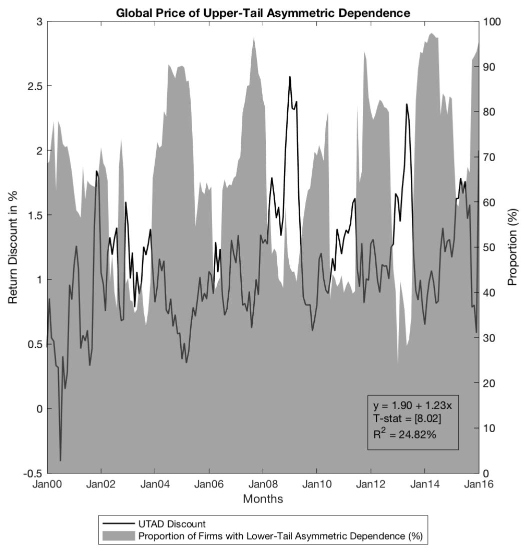
Commonality Effects in the Level and Price of Asymmetric Dependence

I study commonality patterns in the level of asymmetric dependence and its return premium among the individual countries from the sample. In particular, I examine how country levels of AD and return sensitivity to AD are linked with its global and regional values. My research is informed by existing literature on commonality effects among risk factors. Karolyi, Lee, and Van Dijk (2012) study commonality in returns, liquidity, and turnover around the world and find that return commonality is greater during times of high market volatility, large market declines, heightened presence of international and institutional investors, and with positive investor sentiment. Other authors focus on commonalities in liquidity premia (Amihud, Hameed, Kang, and Zhang, 2015; Chordia, Roll, and Subrahmanyam, 2000; Karolyi, Lee, and Van Dijk, 2012). I am the first to explore commonalities in asymmetric dependence and AD pricing across countries.

Price vs 'Supply' of AD



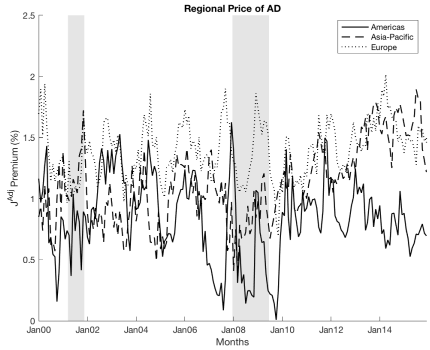
(a) Price of Lower-Tail Asymmetric Dependence



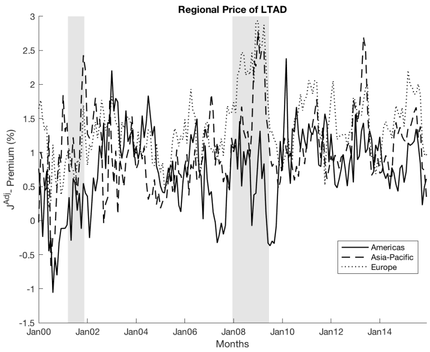
(b) Price of Upper-Tail Asymmetric Dependence

Figure 3.6: The "global" price of lower-tail asymmetric dependence (Figure 3.6(a)) and upper-tail asymmetric dependence (Figure 3.6(b)), calculated in month t as a weighted average of country return premia (discount) attached to LTAD (UTAD) as observed at month t. Shaded areas represent the weighted average of country proportion of LTAD firms. Country weights used to calculate weighted averages reflect the size of country's stock exchange (measured using the number of distinct firms listed in each stock exchange).

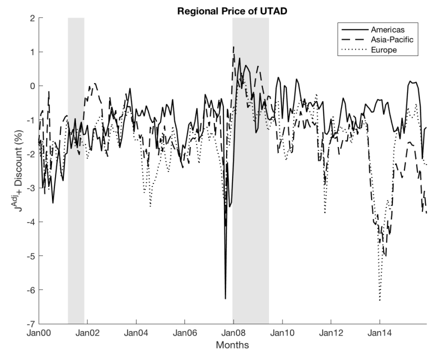
Regional Prices of AD



(a) Asymmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 3.7: Time series of the "regional" price of asymmetric dependence (Panel (a)), lower-tail asymmetric dependence (Panel (b)) and upper-tail asymmetric dependence (Panel (c)). The "regional" price of asymmetric dependence in month t is calculated as a weighted average of country return premia (discount) attached to AD or LTAD (UTAD) as observed at month t for all countries within a region (Americas, Asia-Pacific and Europe). Country weights used to calculate weighted averages reflect the size of country's stock exchange (measured using the number of distinct firms listed in each stock exchange). Shaded areas represent NBER crisis periods.

Commonalities in the Level and Price of Asymmetric Dependence

Table 3.5: This table reports the country-level Commonality regression statistics: the mean regression coefficient, mean t-statistics (in parentheses), median coefficient and the number of positive coefficients across all country regressions. In Panel A, the level of AD from country i is regressed on the global level of asymmetric dependence (J_{gt}^{Adj}), measured as the value-weighted average value of the J^{Adj} across all the countries from the sample (except for country i), the regional level of asymmetric dependence (J_{rt}^{Adj}), measured as the value-weighted average value of the J^{Adj} across all the countries from a given region (except for country i), and the market monthly excess return (R_{mt}). In Panel B, I regress the mean return premium attached to the J^{Adj} or country c in month t (γ_{ct}) on the global level of return premium attached to the J^{Adj} in month t (γ_{gt}), calculated as the equally-weighted average of return premia from month t across all countries from my sample (except for country i), the regional level of return premium attached to the J^{Adj} in month t (γ_{rt}), calculated as the equally-weighted average of return premia from month t across all countries from a given region (except for country i), the global level of asymmetric dependence (J_{gt}^{Adj}) and the regional level of asymmetric dependence (J_{rt}^{Adj}). MSCI World index and the US 1-month T-Bill rate are used as a market and a risk free rate proxy. All returns are in US dollars.

Panel A: Level of AD	J_{gt}^{Adj} (Global Level of AD)	J_{rt}^{Adj} (Regional Level of AD)	R_{mt} (Market Excess Return)
Mean Regression Coefficient	1.009	0.750	0.2175
Mean T-stat	[27.819]	[6.183]	[0.132]
Median Regression Coefficient	1.033	0.711	0.0294
# of positive Regression Coefficients	100%	86%	54%

Panel B: Price of AD	J_{gt}^{Adj} (Global Level of AD)	J_{rt}^{Adj} (Regional Level of AD)	γ_{gt} (Global Price of AD)	γ_{rt} (Regional Price of AD)
Mean Regression Coefficient	-0.006	-0.004	0.601	0.946
Mean T-stat	[0.373]	[0.366]	[3.596]	[4.216]
Median Regression Coefficient	-0.006	-0.003	0.749	0.805
# of positive Regression Coefficients	16%	24%	84%	95%

I find that both the level of AD and return sensitivity to AD display strong commonality patterns. The aggregated firm-level AD observed in different countries is strongly correlated with global as well as regional aggregated firm-level AD. In all the 38 financial markets, the t-statistic associated with the coefficient of the global AD exceeds the value of 20. The market excess return, on the other hand, does not have any strong effect on the firm-level AD in countries examined.

Return sensitivity to AD in the individual countries depends on the global and regional prices of AD, but not on global or regional aggregated firm-level AD. In 82% of countries from my sample (31 out of 38), the global price of AD positively affects country prices of AD. In 35 out of 38 countries, the regional commonality effect is relevant, that is, the coefficient δ_{2c} is positive and significant. The t-statistics associated with the coefficients δ_{1c} and δ_{2c} both exceed the Harvey et al. (2014) hurdle rate of 3.0, see Panel B from Table 3.5.

3.4 Conclusion

This chapter compares the cross section of stock returns across the worlds 38 largest stock exchanges with particular emphasis on the importance of asymmetric dependence for international investors. I find that asymmetric dependence is consistently priced in international equity returns. Indeed, asymmetric dependence is the only factor that is priced in all the in-sample regressions and the vast majority of the out-of-sample regressions.

My main results are consistent across all the countries examined. I find that firms with returns exhibiting lower-tail (upper-tail) asymmetric dependence are associated with a return premium (discount) in all the 38 markets. The evidence of a significant price of asymmetric dependence is consistent with disappointment-averse investors that respond to a relative scarcity of the different types of asymmetric dependence available in the market.

Changes in AD are related to the growth of financial markets relative to GDP and the conditions necessary for the establishment of a business enterprise. I find that the degree of asymmetric dependence rises in countries with increasing market capitalization to GDP. This suggests that the growth in size and importance of financial markets have negative effects that may influence the stability of these markets, as well as the economy as a whole. Moreover, investors become more sensitive to asymmetric dependence and require a higher additional return premium to bear asymmetric dependence risk in countries with a high change in market capitalization to GDP.

Both the level of AD and return sensitivity to AD display strong commonality patterns. Country levels of AD are strongly correlated with global as well as regional levels of AD. The return sensitivity to AD in the individual countries is affected by global and regional prices of AD. These findings suggest that financial markets considered in this study share common factors that affect the time-series development of the firm-level AD and AD pricing.

3.5 Appendix

Country Characteristics

Table 3.6: A list of all country characteristics examined. The Doing Business Distance to Frontier score (DTF) shows the distance of an economy to the "frontier", which is derived from the most efficient practice or highest score achieved on each indicator. I use historical yearly DTF for each indicator available based on the methodology used in March 2017.

Variable Name	Description
Starting a Business DTF	Methodology description: http://www.doingbusiness.org/Methodology/Starting-a-Business. Starting a Business DTF is derived based on all procedures officially required, or Commonly done in practice, for an entrepreneur to start up and formally operate an industrial or commercial business, as well as the time and cost to complete these procedures and the paid-in minimum capital requirement.
Getting Credit DTF	Methodology description: http://www.doingbusiness.org/Methodology/Getting-Credit: Getting Credit DTF measures the legal rights of borrowers and lenders with respect to secured transactions through one set of indicators and the reporting of credit information through another. The first set of indicators measures whether certain features that facilitate lending exist within the applicable collateral and bankruptcy laws. The second set measures the coverage, scope and accessibility of credit information available through credit reporting service providers such as credit bureaus or credit registries.
Protecting Minority Investors DTF	Methodology is described in http://www.doingbusiness.org/Methodology/Protecting-Minority-Investors: Protecting Minority Investors DTF measures the protection of minority investors from conflicts of interest through one set of indicators and shareholders rights in corporate governance through another. The data come from a questionnaire administered to corporate and securities lawyers and are based on securities regulations, company laws, civil procedure codes and court rules of evidence.
Paying Taxes DTF	Methodology description: http://www.doingbusiness.org/Methodology/Paying-Taxes: Paying Taxes DTF records the taxes and mandatory contributions that a medium-size company must pay in a given year as well as the administrative burden of paying taxes and contributions and complying with post-filing procedures. Taxes and contributions measured include the profit or corporate income tax, social contributions and labor taxes paid by the employer, property taxes, property transfer taxes, dividend tax, capital gains tax, financial transactions tax, waste collection taxes, vehicle and road taxes, and any other small taxes or fees. The ranking of economies on the ease of paying taxes is determined by sorting their distance to frontier scores for paying taxes.
Trading Across Borders DTF	Methodology description: http://www.doingbusiness.org/Methodology/Trading-Across-Borders: Trading Across Borders DTF records the time and cost associated with the logistical process of exporting and importing goods. Doing Business measures the time and cost (excluding tariffs) associated with three sets of procedures: documentary compliance, border compliance and domestic transport within the overall process of exporting or importing a shipment of goods.
Enforcing Contracts DTF	Methodology description: http://www.doingbusiness.org/Methodology/Enforcing-Contracts: Enforcing Contracts DTF measures the time and cost for resolving a commercial dispute through a local first-instance court and the quality of judicial processes index, evaluating whether each economy has adopted a series of good practices that promote quality and efficiency in the court system. The data are collected through study of the codes of civil procedure and other court regulations as well as questionnaires completed by local litigation lawyers and judges.

*[h] **Country Characteristics: Continued**

Variable Name	Description
Resolving Insolvency DTF	Methodology description: http://www.doingbusiness.org/Methodology/Resolving-Insolvency: Resolving Insolvency DTF is based on the time, cost and outcome of insolvency proceedings involving domestic entities as well as the strength of the legal framework applicable to judicial liquidation and reorganization proceedings. The data for the resolving insolvency indicators are derived from questionnaire responses by local insolvency practitioners and verified through a study of laws and regulations as well as public information on insolvency systems. Source: Doing Business Indicators, World Bank: http://www.doingbusiness.org
Short selling practiced	A dummy variable equal to 1 if short selling is practiced and zero otherwise. For countries that are not mentioned in Bris et al. (2007), data is filled in based on publicly available information. Source: Bris, Goetzmann, and Zhu (2007)
Law Code Dummy Variables	Identifies the legal origin of the company law or commercial law of each country. Each dummy variable is equal to 1 if the origin of the company law or commercial law of the country is English, French, German or Scandinavian, respectively, and zero otherwise. Source: Djankov, La Porta, Lopez-de Silanes, and Shleifer (2010)
Market capitalization to GDP (%)	Market capitalization of listed domestic companies (% of GDP). Market capitalization (also known as market value) is the share price times the number of shares outstanding (including their several classes) for listed domestic companies. Investment funds, unit trusts, and companies whose only business goal is to hold shares of other listed companies are excluded. Data are end of year values.
Inflation, consumer prices (annual %)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used.
Turnover ratio (%)	Stocks traded, turnover ratio of domestic shares (%). Turnover ratio is the value of domestic shares traded divided by their market capitalization. The value is annualized by multiplying the monthly average by 12.
log(GNI) (constant 2010 US$)	GNI (formerly GNP) is the sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation of output plus net receipts of primary income (compensation of employees and property income) from abroad. Data are in constant 2010 U.S. dollars. In log values.
Risk premium on lending (%)	Risk premium on lending is the interest rate charged by banks on loans to private sector customers minus the risk free" treasury bill interest rate at which short-term government securities are issued or traded in the market.
log(Population), total	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates. Source: World Development Indicators, The World Bank

Factor values

Table 3.7: This table presents mean factor values and its standard deviations (in parenetheses) of all listed firms from country i. At each month, t, I estimate for each firm from country i: J^{Adj}, $J^{Adj}-$, $J^{Adj}+$, β, size ("Log-size"), book-to-market ratio ("BM"), the average past 12-monthly excess return ("Past Ret"), idiosyncratic risk ("Idio"), coskewness ("Cosk") and cokurtosis ("Cokurt") using the past 12 months of daily excess return data. The Amihud (2002) illiquidity factor ("illiq") is estimated using daily data from $t-3$ until t. Factor values are estimated using all data available, a description of the data used is provided in Table 3.1. MSCI World index and the US 1-month T-Bill rate are used as a market and risk free rate proxy for all countries. All returns are in US dollars.

Country i	J^{Adj} (AD)	$J^{Adj}-$ (LTAD)	$J^{Adj}+$ (UTAD)	β	Log-size	BM	Past ret	Idio	Cosk	Cokurt	Illiq
Argentina	-3.125	-6.410	6.014	0.674	18.956	1.637	0.007	0.028	-0.138	1.109	(0.0010)
	(6.640)	(3.745)	(3.767)	(0.484)	(1.958)	(2.686)	(0.049)	(0.012)	(0.201)	(0.997)	(0.0030)
Australia	-2.648	-6.578	6.025	0.592	17.729	0.864	0.012	0.050	-0.054	0.701	34.226
	(7.061)	(4.075)	(3.735)	(0.571)	(2.095)	(0.822)	(0.064)	(0.034)	(0.147)	(0.787)	(135.449)
Austria	-1.629	-6.215	5.988	0.568	19.604	1.662	0.003	0.024	-0.062	1.082	(0.0014)
	(7.082)	(3.875)	(3.944)	(0.514)	(1.747)	(3.078)	(0.037)	(0.015)	(0.187)	(1.352)	(0.0052)
Belgium	-1.912	-6.273	5.882	0.568	19.552	2.540	0.007	0.040	-0.048	1.062	(0.0100)
	(7.048)	(3.982)	(3.918)	(0.585)	(1.805)	(7.688)	(0.046)	(0.076)	(0.168)	(1.132)	(0.0576)
Canada	-2.753	-5.943	5.517	0.458	8.848	0.748	0.007	0.039	-0.073	0.728	(0.0033)
	(6.228)	(3.596)	(3.322)	(0.530)	(8.504)	(1.424)	(0.047)	(0.027)	(0.167)	(1.564)	(0.0118)
Chile	-2.053	-6.323	6.493	0.518	19.866	0.829	0.008	0.020	-0.099	1.463	(0.0407)
	(7.371)	(4.178)	(4.311)	(0.331)	(1.722)	(1.126)	(0.034)	(0.014)	(0.204)	(1.186)	(0.2591)
Denmark	-1.815	-5.961	6.073	0.546	18.915	5.825	0.002	0.029	-0.051	0.944	(0.0025)
	(6.891)	(3.634)	(4.219)	(0.451)	(1.877)	(4.481)	(0.041)	(0.019)	(0.165)	(1.018)	(0.0117)
Egypt	-1.165	-6.568	6.732	0.121	18.615	6.117	0.006	0.027	-0.037	0.205	(0.0008)
	(7.552)	(3.629)	(4.013)	(0.298)	(1.642)	(5.424)	(0.045)	(0.011)	(0.153)	(0.573)	(0.0023)
Finland	-1.639	-5.806	5.705	0.708	19.230	1.818	0.005	0.029	-0.049	1.160	(0.0010)
	(6.556)	(3.463)	(3.614)	(0.524)	(1.778)	(3.304)	(0.038)	(0.020)	(0.160)	(1.082)	(0.0030)
France	-2.509	-6.271	5.817	0.580	19.186	1.771	0.004	0.027	-0.057	1.016	(0.0054)
	(6.726)	(3.769)	(3.643)	(0.516)	(2.148)	(2.639)	(0.038)	(0.017)	(0.159)	(1.136)	(0.0153)
Germany	-2.618	-6.359	5.859	0.477	18.235	0.779	0.001	0.036	-0.038	0.635	(0.0056)
	(6.750)	(3.772)	(3.600)	(0.494)	(1.835)	(0.721)	(0.047)	(0.024)	(0.145)	(0.832)	(0.0192)
Greece	-1.774	-5.857	5.597	0.690	18.151	17.140	0.004	0.036	-0.039	0.963	(0.0214)
	(6.470)	(3.466)	(3.361)	(0.480)	(1.822)	(53.291)	(0.049)	(0.017)	(0.141)	(0.860)	(0.0744)
Hong Kong	-3.395	-6.501	5.601	0.415	18.908	12.074	0.012	0.038	-0.058	0.544	(0.0014)
	(6.466)	(3.878)	(3.238)	(0.447)	(1.772)	(11.983)	(0.059)	(0.021)	(0.142)	(0.666)	(0.0035)
India	-2.824	-5.785	5.371	0.411	16.037	1.833	0.008	0.037	-0.051	0.538	(0.5011)
	(5.915)	(3.326)	(3.129)	(0.387)	(1.698)	(2.894)	(0.060)	(0.014)	(0.135)	(0.580)	(1.2385)
Indonesia	-3.031	-6.649	6.125	0.478	27.646	0.754	0.020	0.041	-0.051	0.619	(0.0000)
	(6.956)	(3.934)	(3.833)	(0.526)	(2.030)	(2.522)	(0.063)	(0.025)	(0.154)	(0.748)	(0.0000)
Ireland	-2.259	-5.559	5.113	0.857	13.756	0.639	0.010	0.023	-0.097	1.809	(0.0001)
	(5.887)	(3.331)	(2.931)	(0.528)	(1.802)	(0.464)	(0.032)	(0.013)	(0.235)	(2.297)	(0.0002)
Italy	-2.596	-6.125	5.493	0.759	19.768	94.465	0.002	0.024	-0.060	1.291	(0.0007)
	(6.341)	(3.486)	(3.247)	(0.461)	(1.828)	(302.010)	(0.037)	(0.011)	(0.157)	(1.061)	(0.0026)

Factor values - Table 3.7 Continued

Country i	J^{Adj} (AD)	$J^{Adj}-$ (LTAD)	$J^{Adj}+$ (UTAD)	β	Log-size	BM	Past ret	Idio	Cosk	Cokurt	Illiq
Japan	-2.062	-5.773	5.391	0.561	19.538	1.020	0.002	0.027	-0.030	0.662	(0.0001)
	(6.222)	(3.398)	(3.175)	(0.604)	(1.654)	(0.709)	(0.034)	(0.012)	(0.150)	(0.923)	(0.0002)
Korea	-2.501	-5.762	5.608	0.520	18.093	1.517	0.010	0.036	-0.066	0.767	(0.0006)
	(6.095)	(3.314)	(3.160)	(0.381)	(1.545)	(1.309)	(0.052)	(0.016)	(0.144)	(0.715)	(0.0019)
Mexico	-2.691	-6.274	6.615	0.884	20.585	11.988	0.005	0.027	-0.125	1.480	(0.0028)
	(7.093)	(3.881)	(4.686)	(0.535)	(1.652)	(10.050)	(0.043)	(0.018)	(0.199)	(1.098)	(0.0089)
Netherlands	-2.357	-6.061	5.808	0.700	19.835	0.842	0.004	0.025	-0.072	1.247	(0.0011)
	(6.619)	(3.671)	(3.710)	(0.514)	(2.131)	(0.728)	(0.036)	(0.016)	(0.168)	(1.339)	(0.0038)
New Zealand	-1.551	-6.207	6.030	0.399	18.345	1.277	0.008	0.028	-0.070	0.778	(0.0210)
	(7.098)	(3.940)	(3.789)	(0.337)	(1.765)	(1.010)	(0.040)	(0.021)	(0.156)	(0.797)	(0.1187)
Norway	-2.737	-6.174	5.742	0.891	19.126	0.943	0.006	0.033	-0.095	1.279	(0.0019)
	(6.541)	(3.695)	(3.688)	(0.551)	(1.718)	(1.189)	(0.051)	(0.019)	(0.177)	(1.066)	(0.0078)
Pakistan	-2.324	-5.925	5.689	0.047	17.045	1.416	0.014	0.033	-0.030	0.080	(1.7841)
	(6.372)	(3.451)	(3.371)	(0.328)	(1.901)	(2.340)	(0.052)	(0.019)	(0.138)	(0.504)	(9.7799)
Peru	-1.981	-7.563	7.805	0.352	18.984	2.368	-0.009	0.041	-0.087	0.855	(0.0025)
	(9.295)	(5.369)	(6.076)	(0.654)	(1.791)	(3.615)	(0.143)	(0.068)	(0.164)	(0.933)	(0.0079)
Philippines	-2.783	-6.748	6.230	0.282	18.356	1.365	0.018	0.038	-0.053	0.378	(0.0235)
	(7.176)	(4.054)	(3.768)	(0.447)	(1.982)	(1.732)	(0.061)	(0.021)	(0.141)	(0.616)	(0.1174)
Poland	-2.629	-6.031	5.535	0.875	17.648	3.335	0.006	0.035	-0.080	1.301	(0.0732)
	(6.247)	(3.407)	(3.228)	(0.510)	(1.961)	(3.186)	(0.053)	(0.020)	(0.167)	(1.004)	(0.2826)
Romania	-1.907	-6.546	7.085	0.598	18.532	5.774	0.007	0.031	-0.080	1.122	(0.0378)
	(7.812)	(3.648)	(5.563)	(0.429)	(2.921)	(5.737)	(0.051)	(0.017)	(0.171)	(1.050)	(0.1337)
Shanghai	-0.717	-5.616	5.477	0.191	19.836	0.829	0.008	0.030	-0.047	0.320	(0.0002)
	(6.439)	(3.226)	(3.466)	(0.304)	(1.279)	(2.521)	(0.044)	(0.012)	(0.149)	(0.604)	(0.0010)
Shenzhen	-0.969	-5.716	5.767	0.211	19.811	3.162	0.006	0.031	-0.055	0.351	(0.0004)
	(6.619)	(3.313)	(3.610)	(0.312)	(0.953)	(2.643)	(0.043)	(0.012)	(0.148)	(0.617)	(0.0033)
Singapore	-2.709	-6.576	6.111	0.501	18.422	3.214	0.011	0.041	-0.051	0.674	(0.0027)
	(7.029)	(4.007)	(3.685)	(0.488)	(1.706)	(6.019)	(0.049)	(0.032)	(0.156)	(0.772)	(0.0063)
South Africa	-2.097	-6.067	5.522	0.709	19.164	6.757	0.011	0.034	-0.069	1.064	(0.0599)
	(6.567)	(3.721)	(3.320)	(0.494)	(2.085)	(6.307)	(0.045)	(0.025)	(0.158)	(0.925)	(0.2708)
Spain	-1.963	-6.178	5.904	0.759	20.272	9.466	0.004	0.024	-0.054	1.305	(0.0002)
	(6.998)	(4.020)	(3.893)	(0.516)	(1.914)	(26.358)	(0.039)	(0.016)	(0.164)	(1.186)	(0.0004)
Sweden	-2.425	-6.038	5.674	0.864	18.685	0.855	0.004	0.034	-0.068	1.307	(0.0092)
	(6.476)	(3.592)	(3.489)	(0.517)	(2.118)	(0.713)	(0.048)	(0.024)	(0.166)	(1.067)	(0.0497)
Switzerland	-1.835	-5.869	5.823	0.528	20.060	1.103	0.004	0.026	-0.054	0.971	(0.0004)
	(6.672)	(3.571)	(3.910)	(0.467)	(1.810)	(1.030)	(0.037)	(0.027)	(0.163)	(0.997)	(0.0015)
Turkey	-0.617	-5.864	6.778	1.050	21.245	1.492	0.002	0.035	-0.086	1.517	(0.0001)
	(7.478)	(3.161)	(5.211)	(0.567)	(5.606)	(1.324)	(0.052)	(0.016)	(0.185)	(1.042)	(0.0004)
UK	-2.292	-6.872	6.220	0.547	18.954	0.907	0.007	0.027	-0.059	0.988	(0.0020)
	(7.451)	(4.167)	(3.873)	(0.471)	(2.122)	(0.840)	(0.046)	(0.020)	(0.166)	(1.053)	(0.0084)
US	-2.259	-5.559	5.113	0.857	13.756	0.639	0.010	0.023	-0.097	1.809	(0.0001)
	(5.887)	(3.331)	(2.931)	(0.528)	(1.802)	(0.464)	(0.032)	(0.013)	(0.235)	(2.297)	(0.0002)

Factor Correlations

Table 3.8: This table presents the range (min, max) of correlations between each factor across all countries examined. At each month, t, I use the past 12 months of daily excess return data to estimate β, β^-, β^+, size ("Log-size"), book-to-market ratio ("BM"), the average past 12-monthly excess return ("Past Ret"), idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj}. The Amihud (2002) illiquidity factor ("illiq") at month t is estimated using daily data from $t-3$ until t. All factors are Winsorised at the 1% and 99% level at each month. A description of the data used to calculate the factor values is provided in Table 3.1. MSCI World index and the US 1-month T-Bill rate are used as a market and risk free rate proxy. All returns are in US dollars.

	β^-		β^+		Log-size		BM		Past ret		Idio		Cosk		Cokurt		Illiq		J^{Adj} (AD)	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
β	0.437	0.787	0.409	0.801	-0.122	0.477	-0.381	0.236	-0.027	0.150	-0.077	0.217	-0.357	0.000	0.313	0.750	-0.259	0.046	-0.112	0.220
β^-			-0.009	0.512	-0.248	0.347	-0.270	0.152	-0.206	0.167	-0.424	0.220	-0.695	-0.288	0.191	0.644	-0.183	0.108	-0.285	0.212
β^+					-0.181	0.386	-0.281	0.187	-0.099	0.129	-0.133	0.115	0.152	0.499	0.257	0.629	-0.182	0.116	0.017	0.184
Log-size							-0.596	0.476	-0.035	0.207	-0.627	0.541	-0.142	0.112	-0.460	0.505	-0.587	0.043	-0.094	0.264
BM									-0.223	0.015	-0.233	0.362	-0.051	0.114	-0.296	0.121	-0.087	0.514	-0.142	0.035
Past Ret											-0.271	0.258	-0.170	0.041	-0.024	0.171	-0.195	0.131	-0.067	0.151
Idio													-0.017	0.248	-0.437	0.002	-0.042	0.508	-0.162	0.281
Cosk															-0.620	-0.044	-0.018	0.076	0.233	0.444
Cokurt																	-0.252	0.063	-0.178	0.150
Illiq																			-0.105	0.074

4

Asymmetric Dependence in Real Estate Investment Trusts: An Asset-Pricing Analysis

4.1 Introduction

Many authors consider real estate investment trusts (REITs) to be defensive assets having a low correlation with market returns, that is having a CAPM β less than one (Chan, Hendershott, and Sanders, 1990; Glascock and Hughes, 1995; Glascock, Michayluk, and Neuhauser, 2004; Howe and Shilling, 1990; Hung and Glascock, 2008). However, more recent research suggests that the dependence structure between REITs and the market is more complex than previously thought (Chong and Miffre, 2009; Clayton and MacKinnon, 2003). For example, Sun, Titman, and Twite (2015) provide evidence that the REIT sensitivity to market returns was particularly high during the global financial crisis of 2007-2008. This is consistent with a broader pattern whereby REIT returns are more highly correlated in market downturns than in upturns (Goldstein, 1999; Knight, Lizieri, and Satchell, 2005).

This asymmetric dependence (AD) between REIT returns and market returns is well documented.[1] Several authors find evidence of AD between returns of well-diversified stock indices and infer that AD is not easily diversified away (Alcock and Hatherley, 2009; Ang and Bekaert, 2002; Erb, Harvey, and Viskanta, 1994; Hartmann, Straetmans, and De Vries, 2004; Hong, Tu, and Zhou, 2007; Longin and Solnik, 2001; Low, Alcock, Faff, and Brailsford, 2013; Patton, 2004). The existence and non-diversifiability of AD implies that CAPM β may not adequately describe the sensitivity of REIT returns to market movements. If REIT investors exhibit

[1]See for example Bianchi and Guidolin (2014); Case, Yang, and Yildirim (2012b); Chatrath, Liang, and McIntosh (2000); Goldstein (1999); Hoesli and Reka (2013); Huang and Wu (2015); Knight, Lizieri, and Satchell (2005); Lizieri and Satchell (1997a,b); Lizieri, Satchell, and Zhang (2007); Patel and Nimmanunta (2009); Rong and Trück (2010); Simon and Ng (2009); Zimmer (2015). The existence of AD is not specific to REIT markets only. There also exists a substantial literature on the existence of AD in the US stock market, see Ang and Bekaert (2002); Ang and Chen (2002); Ang, Chen, and Xing (2006a); Bali, Demirtas, and Levy (2009); Bollerslev and Todorov (2011); Erb, Harvey, and Viskanta (1994); Hartmann, Straetmans, and De Vries (2004); Hatherley and Alcock (2007); Hong, Tu, and Zhou (2007); Longin and Solnik (2001); Low, Alcock, Faff, and Brailsford (2013); Patton (2004); Post and Van Vliet (2006).

preferences for AD, then AD should be priced in US REIT returns independently of the price for CAPM β.

The primary objective of this paper is to determine the price of asymmetric dependence in US REIT returns. This research contributes to the existing literature on REIT return premia by exploring the price that REIT investors attach to lower-tail and upper-tail asymmetric dependence, independently of symmetric, linear dependence (CAPM β). A significant premium for asymmetric dependence is consistent with REIT investors being disappointment averse, rather than risk averse. Given the previously weak empirical support for CAPM β premium (Pai and Geltner, 2007), my thesis may provide useful isights on whether REIT investors are risk averse, disappointment averse, or both.

Asymmetric dependence is particularly important for US REIT investors for a number of reasons. First, REITs are often highly leveraged, which increases the level of AD in equity-holder returns (Alcock and Steiner, 2015). Second, to the extent that AD attracts a return premium, REIT managers may have an incentive to increase their firm's exposure to AD in order to report this return compensation as alpha (Alcock, Glascock, and Steiner, 2013; Diamond and Rajan, 2009; Goetzmann, Ingersoll, Spiegel, and Welch, 2007). Due to the diversified ownership provisions of REIT legislation, investors have few tools to minimize such rent-seeking behavior (Ghosh and Sirmans, 2003). The ultimate tool available to investors is withdrawal of their capital, i.e. price protection. If REIT investors are more likely to use this tool, then AD may be more of a concern for REIT investments compared to other listed securities.

Finally, US REITs are required to distribute at least 90% of their taxable income to investors in order to qualify for reduced corporate tax,[1] as so are less able

[1] 26 US Code, Section 857 - Taxation of real estate investment trusts and their beneficiaries.

to maintain a cash buffer to protect against unfavourable future market conditions (Bradley, Capozza, and Seguin, 1998; Jensen, 1986). REITs are exogenously cash constrained compared to other public firms. An, Hardin, and Wu (2012) highlight that REITs are consequently more sensitive to liquidity crises: *"Without access to bank lines of credit, REITs are at a disadvantage when competing with other firms in making acquisitions."*[1] The effect of market downturns on REITs may be thus more pronounced than the effect of market upturns (Bianchi and Guidolin, 2014; Chong and Miffre, 2009; Goldstein, 1999; Simon and Ng, 2009; Zhou and Anderson, 2013). This increased downside sensitivity can further result in US REIT returns exhibiting lower-tail asymmetric dependence.

It has so far proven difficult to identify the price of AD independently of the price for CAPM β because most of the metrics employed to identify AD do not satisfy strict monotonicity and orthogonality conditions. I use an adjusted version of the J-statistic (Alcock and Hatherley, 2016) that is monotonic, orthogonal to CAPM β, and is size and scale invariant. Consequently, it is ideally suited for exploring AD in an asset-pricing framework. Furthermore, the adjusted J-statistic can distinguish between two different types of AD: lower-tail asymmetric dependence (LTAD), where the correlation between stock and market returns is higher in the lower tail than in the upper tail of the joint-return distribution, and upper-tail asymmetric dependence (UTAD), where the correlation is higher in the upper tail than in the lower tail. The secondary objective of this paper is to determine the price sensitivity of US REITs to LTAD and UTAD, respectively.

Ultimately, investor preferences will determine whether or not AD is priced in the US REIT market. Disappointment-averse investors with state-dependent

[1]During the 2008-2009 financial crisis, the REIT market experienced a dramatic decline in market value. The FTSE NAREIT U.S. Real Estate Index fell from its index value of 213.68 in January 2007 to 63.41 in March 2009 (Case, Hardin, and Wu, 2012a).

preferences, such as those described by Skiadas (1997), may demand a return premium to compensate for LTAD exposure. Elation-seeking investors with state-dependent preferences may accept a return discount for holding a UTAD asset. The J^{Adj} statistic captures return characteristics consistent with the Skiadas (1997) framework of investor preferences.

I find strong empirical evidence that investors in US REITs demand a significant price for AD exposure. US REITs with LTAD attract a risk premium and US REITs exhibiting UTAD trade at a discount independently of the price of the CAPM β. The typical premium for LTAD in US REITs is 1.3% per annum and the typical discount for UTAD in US REITs is 5.8% per annum. My findings are robust to controlling for a large number of commonly used REIT characteristics. The level of AD can predict US REIT returns up to three months ahead. Interestingly, I find no evidence that the CAPM β is priced in the cross section of US REIT returns. This finding is consistent with Pai and Geltner (2007), who claim that factors important for investors in US REITs are largely different from those relevant for investors in US equities. This is true for most of the standard risk factors. Nevertheless, I find that AD is relevant for investors in US REITs as well as US listed equities. Moreover, AD is the only covariate considered that has a t-value higher than the Harvey, Liu, and Zhu (2014) critical value of 3.0.

The third contribution of this paper is to analyze the temporal trends of the level and price of AD in US REIT returns. The level of both LTAD and UTAD steadily increased until the 2007-2008 financial crisis. The level of LTAD and UTAD has been decreasing since the global financial crisis. The price of both LTAD and UTAD peaked during the crisis but remains a significant factor.

My findings have important implications not only for asset pricing, but also for REIT cost of capital, internal capital allocation, strategic asset allocation, financial risk management, portfolio management and performance assessment. Based on these results, REIT investors do not value the CAPM β but place a considerable premium (discount) on REITs exhibiting LTAD (UTAD). REIT capital allocation and financing decisions are unique and differ substantially from industrial equities. This may explain why investors in REITs value firm-specific information differently.

This chapter is organized as follows. Section 4.2 describes the data and empirical design used to empirically examine my hypotheses. Section 4.3 presents the main empirical results and identifies the temporal trends in AD pricing. I particularly explore the role of AD during the 2007-2008 financial crisis in Section 4.4 and verify the robustness of my results in Section 4.5. Section 4.6 concludes.

4.2 Data and Empirical Design

I use continuously compounded daily total returns of all NYSE-listed REITs described by CRSP database.[1] Data starts in January 1992 with the introduction of the umbrella partnership REIT (UPREIT) regulation and ends in December 2013. I restrict the data sample to common shares of listed US REITs (share code 18) with exchange code equal to 1 (NYSE only). I apply a liquidity rule to remove REIT time series with more than 50% of zero or missing daily returns. The final sample consists of 373 distinct REITs with 792,510 firm-return observations.

I collect daily data on permno, price, holding period return and number of shares outstanding. I collect book value data using the CRSP/Compustat Merged database for the unique permno identifiers. I retrieve the Total Common/Ordinary

[1] I limit the sample to NYSE only due to differing listing requirements of the remaining stock exchanges in the US. NYSE provides a market for well-established companies, which are expected to have a more stable stock price development. NYSE offers the highest level of disclosure of information of all the stock exchanges in the US, and contains relatively large companies with a more stable performance and operating history.

Equity data. I proxy the risk free rate by the 1 month T-bill rate collected from the Kenneth R. French Data Library. The market return proxy is the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks also collected from the Kenneth R. French Data Library. The excess daily returns are computed as the difference between the daily holding return and the daily risk free rate.

I estimate the risk premia using both in-sample and out-of-sample estimation methods. I employ the Ang et al. (2006a) contemporaneous regression method to generate in-sample estimates of the risk premia for each factor. I run the in-sample cross-sectional regressions each month rolling forward using a 12 month window. The short rolling window allows us to account for time variations in risk premia or the individual risk factors. For each month t, I calculate the relevant variables for all stocks with data in months $t-12$ to t. I estimate the J^{Adj}-statistic using daily excess returns following the definition from equation (5.40) and using the following levels of exceedances $\delta = \{0, 0.2, 0.4, 0.6, 0.8, 1\}$, consistent with Hong et al. (2007).

I use continuous compounding to convert daily excess returns into monthly excess returns. I calculate market capitalization as the absolute value of the product of the close share price and total shares outstanding. Firm size is then the average log value of firm's market capitalization over the 12 months. Book-to-market ratio is the average ratio of the book value of equity to the market capitalization over the 12 months. Firm coskewness and cokurtosis are estimated using daily observations from the 12 months of data. The idiosyncratic risk is proxied by the standard deviation of CAPM residuals estimated on daily data from the 12 months.

I employ the Fama and MacBeth (1973) intertemporal regression method to generate out-of-sample estimates of the risk premia for each factor. For each month t, I calculate the relevant predictors on data from $t-12$ to t. Mean monthly excess returns from $t+1$ are regressed on information from the preceding 12 months, consistent with Fama and MacBeth (1973).

Finally, I explore the predictive ability of the J^{Adj} (out-of-sample) using future three-month (six-month) mean monthly-excess returns. All relevant variables are calculated on data from $t-12$ to t and mean excess returns are calculated on data from t to $t+3$ ($t+6$).

In all the regressions, I apply the Newey and West (1987b) procedure to test for statistical significance with overlapping windows and use the Newey and West (1994b) automatic lag selection.

4.3 Asymmetric Dependence Risk Premium

Descriptive Statistics

Descriptive statistics for the variables used in the cross-sectional regressions are presented in Table 4.1. The mean J^{Adj} is negative (-1.575). This finding is consistent with Huang and Wu (2015), who find that LTAD is more prevalent in US REITs. Knight et al. (2005) provide similar conclusions in the UK REIT market. My sample is comprised of 66% of LTAD US REITs with a mean value of $J^{Adj}-$ of -5.331 and 34% US REITs that exhibit UTAD with a mean $J^{Adj}+$ of 5.140.

In my sample, the equally-weighted average monthly excess return on US REITs is 1.0% and the equally-weighted average CAPM β is 0.643. The equally-weighted average β, β^- and β^+ have similar values (0.643, 0.674 and 0.632, respectively). This suggests a lack of asymmetry in the linear dependence of US REIT returns with those of the market. Taking together, these statistics suggest that there is a significant AD despite no evidence of asymmetry in the linear dependence.

Factor Correlation and Double Sorted Portfolios

The correlation between the individual risk factors is presented in Table 4.2. There is a relatively high degree of correlation between β and cokurtosis (65%), size and cokurtosis (55%) and β and size (49%). I test for potential multicollinearity using the variance inflation factor index (VIF) (Belsley, 1991) and find no evidence of a strong or moderate multicollinearity (VIF < 5 for all the variables). The correlations between the J^{Adj} and other covariates are unremarkable with a possible exception of coskewness. In order to better understand the correlation structures, I double sort the sample into J^{Adj} and coskewness, as well as J^{Adj} and β deciles.

The results from the double-sorting procedure are described in Table 4.3, where Panel A depicts mean excess returns sorted into β and J^{Adj} and Panel B presents mean excess returns sorted in coskewness and J^{Adj}. When considering the double sorts in coskewness and J^{Adj} deciles, mean excess returns are monotonically decreasing in J^{Adj} deciles and relatively constant across the coskewness deciles. After controlling for J^{Adj}, coskewness does not appear to have any significant effect on excess returns. The difference in excess returns between the lowest and the highest J^{Adj} decile is positive for most of the coskewness deciles. The mean excess returns are monotonically decreasing in J^{Adj} deciles. That is, a higher value of AD is associated with a lower excess return.

When considering mean excess returns sorted in β and J^{Adj} deciles, there appears to be little evidence of a correlation between β and excess returns. The relation between the J^{Adj} is more straightforward as for almost every β decile, the difference in excess returns between the lowest and the highest J^{Adj} decile is positive for most of the β deciles.

The Price of Asymmetric Dependence

I now turn my attention to the in-sample estimates of the risk premia from the contemporaneous Ang et al. (2006a) regressions. After controlling for β, size, book-to-market ratio, past returns, idiosyncratic risk, coskewness and cokurtosis, the J^{Adj} is negatively correlated with contemporaneous excess returns, see Table 4.4. That is, AD in REIT returns are associated with a significant price. This is consistent with REIT investors demanding a risk premium for LTAD and REIT investors willing to accept a discount for UTAD. This price of AD is independent of any premium attached to β. The J^{Adj} is strongly significant having the highest t-statistic of all risk factors. The J^{Adj} is the only risk factor considered with a t-statistic that exceeds the Harvey, Liu, and Zhu (2014) level of 3.0.[1]

The typical risk premium for AD in US REITs, where I define a typical price (premium or discount) to be the factor price sensitivity multiplied by the average factor value, $-0.004 \times (-1.575)$, is 0.6% per annum. Huang and Wu (2015) show that by accounting for AD in US REITs, an investor can outperform the market and generate higher excess returns that the market. My findings go one step further and show that this is also reflected in the price of individual US REITs.

The significant factors from the Ang et al. (2006a) contemporaneous regression are J^{Adj}, firm size, past excess return and cokurtosis. Interestingly, neither the CAPM β nor idiosyncratic risk are significant in the cross section of US REIT returns. This is despite of high levels of idiosyncratic risk that real-estate funds managers often need to to manage.

At least 75% of all assets in REITs must be invested in real estate, cash or US Treasury,[2] which may lower the ability to diversify risk. Nevertheless, I find that

[1]This t-statistic level of 3.0 is set by Harvey et al. (2014) to account for data mining, correlation among the tests and missing data issues.

[2]US Code 26, Section 856.

idiosyncratic risk is insignificant implying that US REIT investors do not value idiosyncratic risk (Campbell et al., 2001; Fu, 2009; Merton, 1987).

I estimate the out-of-sample sensitivity of future one-month excess returns to the AD measure (J^{Adj}) using the Fama and MacBeth (1973) intertemporal regression method. I find that the J^{Adj} is also significant in the out-of-sample regression and the coefficient associated with J^{Adj} is (-0.005) and the typical price attached to average level of J^{Adj} is $(-0.005) \times (-1.575)$, that is 0.8% per annum. The coefficient of the J^{Adj} a from the out-of-sample regression is the only risk factor with a t-statistic that exceeds the Harvey, Liu, and Zhu (2014) critical value of 3.0.

The CAPM β is not significant in the in-sample regression but is significant in the out-of-sample specification, although it has a negative coefficient. Indeed, the CAPM β coefficient is negative in all my regressions, whether it is significant or not. The out-of-sample regression procedure yields qualitatively similar results to the in-sample regression, which suggests that my results are robust to different regression specifications.

I also explore the power of J^{Adj} to predict future excess returns over longer investment horizons, Table 4.4, columns 3 and 4. I find that the J^{Adj} can predict excess returns up to three months ahead.

Lower-Tail Asymmetric Dependence vs Upper-Tail Asymmetric Dependence

I quantify the price associated with LTAD and UTAD separately and re-run the regressions using the $J^{Adj}-$ and $J^{Adj}+$ measure of LTAD and UTAD. After controlling for other factors, my measure for LTAD (J^{Adj}-) and UTAD ($J^{Adj}+$) are both contemporaneously and intertemporally correlated with excess returns, see Table 4.5, columns 1 and 2. The J^{Adj}- ($J^{Adj}+$) is positively (negatively) correlated with US REIT excess returns. This implies that a higher degree of LTAD (UTAD) leads to higher (lower) excess returns. The typical premium for LTAD in US REITs is 1.3% and the typical discount for UTAD in US REITs is 5.8%. The premium for LTAD and discount associated with UTAD compares favorably with the typical premium for AD of 0.6% and is substantial compared to the commonly assumed market price of risk of 6.0% (Fernandez, Linares, and Fernández Acín, 2014).

My findings are consistent with investors with state-dependent preferences, where outcomes in events that did not occur also affect attitudes towards outcome that occurred. This is different from risk-aversion, which is independent across states. In paticular, the significant premium (discount) for LTAD (UTAD) is consistent with disappointment-averse (elation-seeking) REIT investors possessing a family of conditional preferences as described by Skiadas (1997). Ang et al. (2006a) propose an alternative measure of disappointment, downside β, which is consistent with investors endowed with Gul (1991) preferences.

The main difference between the Skiadas (1997) and Gul (1991) preferences is entrenched in the identification of the conditional preference relations. Gul (1991) endows investors with a single Savage preference relation and denotes disappointment relative to the certainty equivalent of the investment return distribution. Skiadas (1997) recognises that an agent may, for example, experience significant disappointment in the event of an extreme market drawdown and little or no disappointment in the event of a slight market drawdown. Skiadas (1997) therefore assumes a family of conditional preference relations while Gul (1991) works with a single preference relation.

The conditional CAPM βs are consistent with investors endowed with Gul (1991) preferences, in which the conditional measure of linear dependence is measured using a certainty equivalent, e.g. conditioning on market excess return being lower (market downturn) or greater (market upturn) than zero. The J^{Adj}, on the other hand, assumes that investors have Skiadas (1997) preferences, because the J^{Adj} is measured using conditional exceedance correlations with a family of exceedances.

The conditional βs are insignificant, and the $J^{Adj}-$ and $J^{Adj}+$ are both significant in the in-sample Ang et al. (2006a) regressions, Table 10. Out of sample, the $J^{Adj}+$ is significant in predicting excess returns up to three months ahead. My results suggest that US REIT investors are endowed with a family of state-dependent preferences, as described by Skiadas (1997). I provide further discussion and comparison of the two competing measures of asymmetric dependence in the robustness Section 4.5.

I illustrate relative risk premia of US industrial equities and US REITs in Table 4.6. The CAPM β is not priced in US REITs, but is significant in US equities. This implies that the standard mean-variance preference framework is not well-represented by US REIT investors. The finding of insignificant CAPM β is consistent with Pai and Geltner (2007), who claim that factors important for investors in US REITs are largely different from those relevant for investors in US equities. Investors in REITs are more concerned with asymmetric dependence rather than linear dependence. This finding is consistent with investors using pricing mechanisms to protect against risk.

AD measured by the J^{Adj} is relatively more important for REIT investors than industrial equity investors since AD is the only factor significant in all the pricing regressions for REITs (except size and momentum). This has important implications for cost of capital of US REITs. The price of AD is likely to represent a greater proportion of US REIT cost of capital relatively to the cost of capital of

US industrial equities.

Based on my results, REIT investors do not value the symmetric dependence (CAPM β) but place a considerable premium (discount) on REITs exhibiting LTAD (UTAD). For a US REIT exhibiting lower-tail asymmetric dependence in returns, neglecting the information about the level of asymmetric dependence may lead to serious underestimation of firm cost of capital. Without the AD information, REIT managers may accept projects that will ultimately lead to a destruction of shareholders' wealth. My findings have important implications not only for cost of capital but also for internal capital allocation, strategic asset allocation, financial risk management, portfolio management and performance assessment.

I further test the predictive ability of $J^{Adj}-$ and $J^{Adj}+$ using three-month and six-month future returns. The $J^{Adj}+$ can predict excess returns up to three months ahead. The $J^{Adj}-$ is significant only in the in-sample regressions, whereas the $J^{Adj}+$ is significant in all of the regressions except the six-month predictive regression, see Table 4.5.

The traditional tests of stock return predictability may reject null hypothesis too frequently if the predictor variable is persistent (Campbell and Yogo, 2006). In all my regressions, I account for the artificial persistence created by the presence of overlapping data by incorporating the Newey and West (1987b) procedure to calculate t-statistics with the Newey and West (1994b) automatic lag selection method to determine the lag length.

In addition, I also examine potential persistence in the J^{Adj} by estimating the coefficients of the autoregressive (AR) process of J^{Adj} for each US REIT in my sample. I use non-overlapping estimates of J^{Adj} calculated using daily data from 12-month rolling window periods, Figure 4.1. There is no significant AR coefficient, hence I accept that the J^{Adj} is not persistent. Therefore, my results are robust to

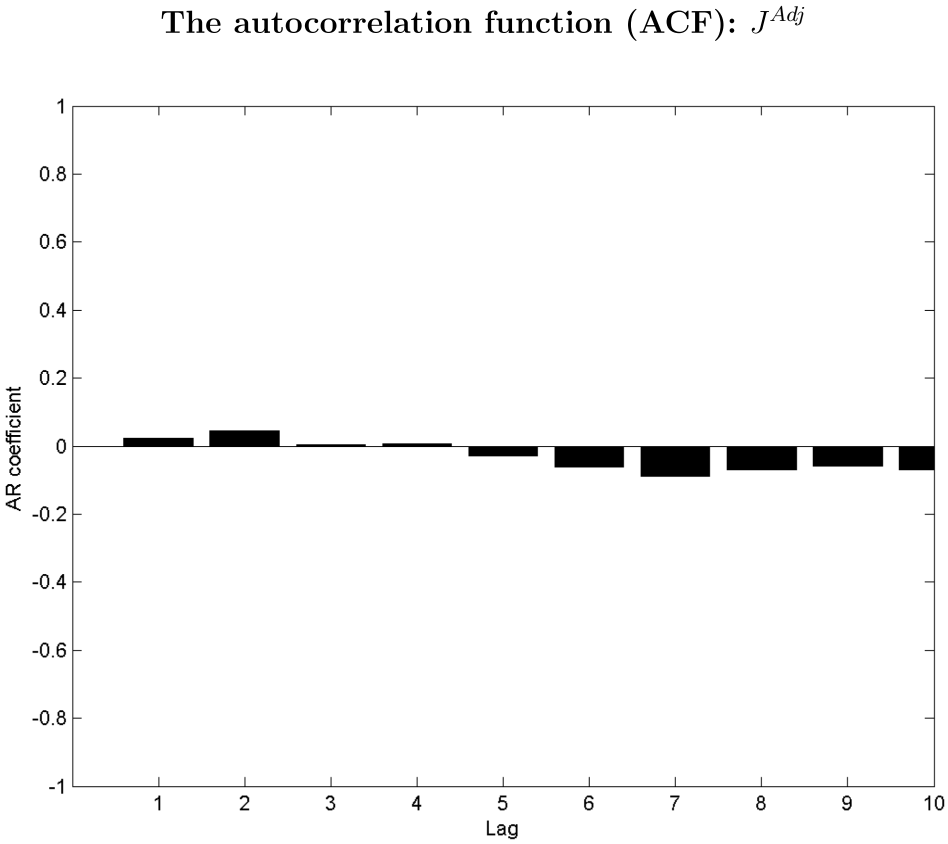


Figure 4.1: The autocorrelation function is computed using a J^{Adj} computed on 12-month non-overlapping periods using daily excess returns. One lag represents a 12-month period. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013.

any persistence concerns.

LTAD and UTAD Migration Probability

I now explore the empirical probability that a US REIT with past LTAD continues to exhibit LTAD. This is not the same as persistence. Here I are only concerned with migrations between the LTAD and UTAD firm-return observations. This information is important from the investor perspective as LTAD is related with a return premium and UTAD attracts a return discount. The information about whether REIT is LTAD or UTAD in a given time period thus completely changes the outlook on return prediction. I estimate the migration probabilities between LTAD and UTAD as follows. First, I use non-overlapping 12-month periods of daily data to estimate $J^{Adj}-$ and $J^{Adj}+$. In the next step, I calculate migration probabilities for each US REIT from the sample individually. Table 4.7 presents mean migration probabilities between LTAD ($J^{Adj}-$) and UTAD ($J^{Adj}+$) firm characteristics.

I find that if a US REIT exhibits LTAD, it has a 70.95% probability of being LTAD twelve months in the future. US REITs exhibiting UTAD are approximately equally likely to be UTAD in twelve months (with 49.87% probability). This implies that the LTAD characteristic is more stable than the UTAD characteristic.

Temporal Trends in AD Pricing

The Skiadas (1997) framework of disappointment-averse investor preferences is state-dependent, which implies that investor sensitivity to AD may change over time. If investor perception of investment outcome changes over time, it may lead to time-series variations in AD.

The level of lower-tail and upper-tail asymmetric dependence of US REITs both rise to a peak and then start to decline suggesting a change in the temporal trend in the level of AD, see Figure 4.2. The risk premium associated with LTAD is relatively stable with a slight decrease in the last years of the sample. The discount attached to UTAD is steadily decreasing since 2000. The market risk premium has increased since 2009 but still remains insignificant in explaining excess returns.

The temporal development of AD risk variations suggests an existence of a structural break around the 2007-2008 financial crisis. The vertical line in Figures 4.2 and 4.3 corresponds to the failure of Lehman Brothers in September 2008. The changes in AD level and price before and after the crisis are further analyzed

Time Variations: Mean Factor Loadings

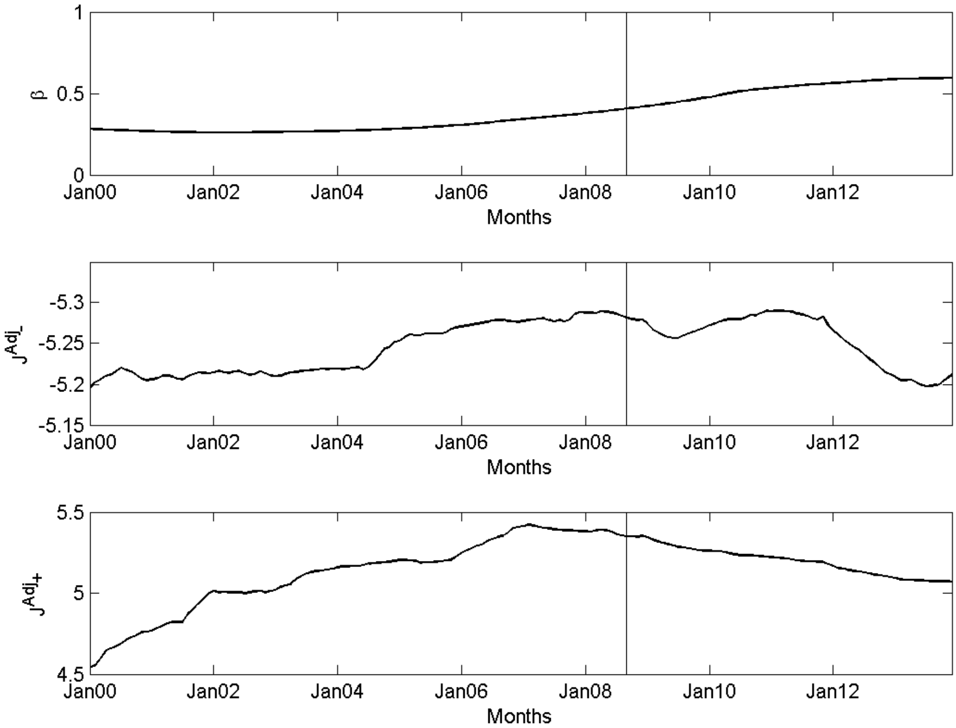


Figure 4.2: This figure depicts the mean factor loading for β, $J^{Adj}-$ and $J^{Adj}+$ at a given month, t, between January 2000 and December 2013 using the past 12 months of daily excess returns. I proxy the market portfolio with the NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. The estimate is calculated using all historical data up to and including time t. The vertical line corresponds to the failure of Lehman Brothers in September 2008.

in Section 4.4.

4.4 US REITs Asymmetric Dependence and the 2007-2008 Financial Crisis

The US REIT market was severely hit by the 2007-2008 financial crisis with a 60% decrease in The National Association of Real Estate Investment Trusts (NAREIT) All Equity Index over the period from September 2008 until February 2009 (Sun et al., 2015). This fall in REIT market value is substantial compared to the decrease in the National Council of Real Estate investment Fiduciaries (NCREIF) Property index of 15% over the same time period.

A number of authors study the performance of REITs during the 2007-2008 financial crisis. Zhou and Anderson (2012) provide evidence that extreme risks are higher in REIT markets relative to stocks, which is even more pronounced after the crisis. An, Wu, and Wu (2015) suggest that the the increased crash risk of REITs after the crisis is due to the changing ownership structure of REITs. They find that with a higher institutional ownership (from 34% in 1994 to 75% in 2011), crash risk for REIT stocks becomes significantly higher relatively to non-REIT stocks. Besides the increased exposure of REIT investors to risk, the diversification benefits of REITs have changed considerably over time and practically vanished in the crisis (Huang and Zhong, 2013; Knight et al., 2005).

Existing literature provides several explanations for this change in REIT-return behavior. Das, Freybote, and Marcato (2015) argue that there was a structural change in the investor decision-making process around the crisis. Before the crisis, institutional investors in REITs created their investment decisions based on sentiment in the private market. During and after the crisis, investors switched their capital from illiquid private markets to more liquid REIT markets (Das et al., 2015). Zhou and Anderson (2013) claim that during the crisis, investors switched from passive externally-managed entities into active self-managed ones and became more responsive to market conditions. The investor herding behavior is stronger in declining markets and during turbulent conditions (Zhou and Anderson, 2013) and the market value of liquidity increased significantly during the crisis (Hill, Kelly, and Hardin III, 2012).

As a consequence of the 2007-2008 financial crisis, the US Government introduced new rules to issue elective stock dividends to help satisfy the dividend requirement of REITs. Devos, Ong, Spieler, and Tsang (2013) study the impact of these rules on REIT dividend policy and find that only 17 REITs used these rules and there was no difference in cash flows between REITs that issued these selective dividends compared to the REITs that did not. According to Case et al. (2012a), it is rather the level of leverage that influences the decisions to pay stock dividends instead of cash flow levels among US REITs. Moreover, (Sun et al., 2015) find that REITs with higher debt to asset ratios and shorter maturity fell more during the 2007-2008 financial crisis.

Because of the evidence of a widespread impact of the 2007-2008 financial crisis on US REITs, I examine whether the level of AD and the investor sensitivity to AD changed after the crisis. I choose the collapse of Lehman Brothers in September 2008 as my structural break point between the two sub-samples. I summarize the mean levels and standard deviations of CAPM β, J^{Adj}, $J^{Adj}-$ and $J^{Adj}+$ in the "pre-crisis" (before September 2008) and "post-crisis" (after September 2008) periods in Table 4.8. The mean CAPM β in the pre-crisis period was 0.433 while the post-crisis mean CAPM β is 1.228. This finding suggests that after the 2007-2008 financial crisis, US REITs became less defensive instruments and the diversification benefits have decreased, which is consistent with empirical findings of Huang and Zhong (2013) and Knight et al. (2005). This difference in mean β before and after the crisis is significantly different with p-value lower than 0.01%, tested using the two-sample T-test for difference in means with unequal standard deviations, see Table 4.8.

The level of asymmetric dependence (both LTAD and UTAD) has decreased after the crisis. The mean value of J^{Adj} was -1.935 before the crisis and -0.536 after the crisis, which suggests that the asymmetries in exceedance correlations decreased. The mean J^{Adj} is significantly different before and after the crisis. The mean factor sensitivity towards J^{Adj} and $J^{Adj}-$ is also significantly lower. However, the sensitivity to $J^{Adj}+$ remains unchanged after the crisis. The results from the tests of significant differences in means for factor levels and factor sensitivities of CAPM β, J^{Adj}, $J^{Adj}-$ and $J^{Adj}+$ are summarized in Table 4.8.

The level of AD as well as AD sensitivity have decreased after the crisis. This change in the REIT risk-return characteristics is consistent with findings of other authors (Huang and Zhong, 2013; Knight et al., 2005). Nevertheless, the J^{Adj} still remains one of the few significant risk factors explaining the cross section of US REIT returns.

4.5 Robustness Checks

To ensure the robustness of the evidence of AD in US REIT returns, I employ various checks using alternative downside measures and alternative regression specifications.

Alternative downside measures

Ang et al. (2006a) build upon the Gul (1991) preference theory to rationalize investor incentives for downside β (β^-) and upside β (β^+). In the Gul (1991) framework, state-dependent investors may feel disappointed if an investment outcome is worse than the certainty equivalent of the investment return distribution. There is only one reference point (the certainty equivalent) that differentiates between bad outcomes and good outcomes, which is consistent with the definition of the downside and upside β.

I define the downside and upside β as $\beta^- = \text{cov}(R_i, R_m|R_m < 0)/\text{var}(R_m|R_M < 0)$ and $\beta^+ = \text{cov}(R_i, R_m|R_m > 0)/\text{var}(R_m|R_M > 0)$, respectively. The downside and upside βs are similar in mean (0.677 vs 0.627) and standard deviation (0.570

vs 0.571), Table 4.1. There is no evidence that for a difference in linear dependence of US REIT returns in the market downturns than upturns.

I compare the two downside risk measures, J^{Adj} and β^{-}, in several ways. First, I double sort US REIT monthly excess returns into β^{-} deciles and then into J^{Adj} deciles in Table 4.9, Panel A. The mean monthly excess returns in β^{-} deciles are relatively constant. There is therefore no evidence that β^{-} capture any valuable information or is valued by investors. The difference in excess returns between the lowest and the highest J^{Adj} decile is positive in most of the β^{-} deciles, which suggests that J^{Adj} is a relevant risk factor independent from β^{-}. The correlation between the J^{Adj} and the downside β is less than 5%, which implies that the value of J^{Adj} provides a different information than downside β.

I replicate the same procedure for β^{+} in Table 4.9, Panel B. Mean excess returns are not monotonic in β^{+} and the difference in mean excess returns between the lowest and the highest J^{Adj} decile is again positive in most of the β^{+} deciles. The J^{Adj} is superior to the downside and upside β in explaining the cross-sectional return variations.

Further, I include β^{-} and β^{+} into the value-weighted in-sample cross-sectional regressions and report my results in Table 4.10. Regression I from Table 4.10 contains the conditional β measures and control variables whereas Regressions II and III from Table 4.10 use the conditional βs, control variables as well as the J^{Adj} or $J^{Adj}-$ and $J^{Adj}+$, respectively, as variables explaining US REIT excess returns. Both β^{-} and β^{+} are insignificant in all the regressions. On the other hand, J^{Adj} is significant with a t-statistic that exceeds the Harvey et al. (2014) t-statistic level of 3.0 in Regression II from Table 4.10.

My results suggest that the marginal price-setting investor is not endowed with a set of Gul (1991) preferences (β^{-} and β^{+} are insignificant). However, I find a strong evidence consistent with the marginal price-setting investor endowed with a family of conditional preferences as described by Skiadas (1997).

Alternative regression specifications

I provide several additional tests to verify the robustness of the results. In Table 4.11, I estimate equally-weighted in-sample cross-sectional regressions and conclude that the J^{Adj} is significant in the equally-weighted regressions.

Next, I explore the effect of US REIT stock return volatility on my results. I exclude the top quintile, decile and vigintile of the most volatile stock returns, re-estimate the out-of-sample cross-sectional regressions and summarize results in Table 4.12. The main results are qualitatively robust to the exclusion of the most volatile US REIT stocks.

In the last test, I change the specification of the rolling window period and use six months to five years of data with daily, weekly and fortnightly frequency to validate results. The CAPM β remains insignificant across all my regressions from Tables 4.13 and 4.14.

My results remain qualitatively unchanged when using alternative data specification. The coefficient associated with the J^{Adj} is significant and negative in all the regressions from Tables 4.13 and 4.14.

4.6 Conclusion

REITs are generally considered to have a low correlation with the market, which provides desirable diversification qualities. I provide new evidence that shows that these diversification benefits are diminished for most of US REITs because of existence of the lower-tail asymmetric dependence. I also quantify investor sensitivity to this asymmetric dependence in the US REITs market. I find a strong empirical evidence that AD in US REIT returns are related with a significant price.

This is consistent with the theory of disappointment aversion described by Skiadas (1997).

My main results suggest that the marginal price-setting disappointment-averse investor demands a premium to hold a REIT exhibiting LTAD averaging at 1.3% per annum. The typical return discount associated with UTAD is 5.8% per annum, which suggests that US REIT investors are willing to accept a substantially lower return in favor for holding a UTAD asset. The price of AD (both LTAD and UTAD) is independent from the CAPM β. Interestingly, I find that neither the CAPM β nor idiosyncratic risk are priced in US REIT returns.

Asymmetric dependence is a significant factor explaining US REIT returns in the in-sample, out-of-sample and predictive regressions with future returns of up to three months ahead. The J^{Adj} is the only significant covariate considered with a t-statistic higher that the Harvey et al. (2014) critical value of 3.0. The statistical significance is strong and the results are robust to various changes in regression specifications, which implies that investors value AD in the cross section of US REIT returns.

Descriptive statistics (1992-2013)

Table 4.1: This table summarizes the mean, standard deviation, minimum, 25th percentile, median, 75th percentile and maximum for all variables in the data set. All variables are estimated at each month, t, using the next 12 months of daily excess return data. Returns ("Ret") are estimated as the average of the next 12 monthly excess return. We restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. I provide summary statistics for β, J^{Adj}, $J^{Adj}-$ and $J^{Adj}+$ in two sub-samples, before September 2008 covering the "pre-crisis" period and after September 2008 denoting the "post-crisis" period.

	Mean	Std	Min	25th	50th	75th	Max
Ret	0.010	0.030	-0.200	-0.002	0.010	0.022	0.341
Log-size	12.859	1.769	7.230	11.857	13.068	14.097	17.650
BM	0.631	1.249	-26.553	0.419	0.622	0.857	16.983
β	0.643	0.603	-2.378	0.206	0.444	1.015	7.385
β^-	0.674	0.617	-6.677	0.268	0.596	1.014	5.251
β^+	0.632	0.734	-3.143	0.159	0.462	1.078	12.352
Idio	0.019	0.017	0.006	0.011	0.014	0.021	0.390
Cosk	-0.081	0.199	-1.416	-0.180	-0.063	0.045	0.779
Cokurt	1.755	1.533	-2.664	0.627	1.409	2.558	9.916
J^{Adj}	-1.575	5.897	-25.254	-5.600	-2.839	3.307	26.220
$J^{Adj}-$	-5.331	3.135	-25.254	-6.932	-4.745	-3.036	-0.084
$J^{Adj}+$	5.140	3.011	0.066	2.961	4.543	6.687	26.220
β							
Before 09/2008	0.433	0.428	-2.378	0.162	0.308	0.618	3.258
After 09/2008	1.228	0.639	-0.767	0.835	1.165	1.537	7.385
J^{Adj}							
Before 09/2008	-1.935	5.982	-25.254	-5.918	-3.257	3.010	26.220
After 09/2008	-0.536	5.533	-22.770	-4.423	-1.275	3.766	23.788
$J^{Adj}-$							
Before 09/2008	-5.445	3.110	-25.254	-7.065	-4.874	-3.162	-0.172
After 09/2008	-4.926	3.192	-22.770	-6.424	-4.173	-2.632	-0.084
$J^{Adj}+$							
Before 09/2008	5.494	3.128	0.113	3.226	4.889	7.148	26.220
After 09/2008	4.458	2.641	0.066	2.553	3.975	5.781	23.788

Factor Correlation

Table 4.2: This table presents the correlation between each factor. We restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. At each month, t, I estimate β, β^{-}, β^{+}, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj} estimated using the next 12 months of daily excess return data, and size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret") computed as at time t. Returns ("Ret") are estimated as the average of the next 12 monthly excess return. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All factors are Winsorized at the 1% and 99% level at each month.

	β	Log-size	BM	Past Ret	Idio	Cosk	Cokurt	J^{Adj}	Ret
β	1	0.486	0.012	-0.003	0.219	0.033	0.651	0.215	0.087
Log-size		1	-0.079	0.081	-0.397	-0.016	0.549	0.240	-0.025
BM			1	-0.099	0.138	-0.006	-0.038	-0.064	0.090
Past ret				1	-0.306	-0.133	0.124	0.029	0.050
Idio					1	0.106	-0.114	-0.062	-0.084
Cosk						1	-0.330	0.432	0.032
Cokurt							1	0.141	0.056
J^{Adj}								1	-0.017
Ret									1

The Time Series Average Returns for Double Sorted Portfolios

Table 4.3: For a given month, I first sort stocks into β deciles, and then into J^{Adj} deciles within each characteristic decile in Panel A. In Panel B (C), I first sort stocks into coskewness (size) deciles and then into J^{Adj} deciles within each characteristic decile. Dependence ranges from low (group 1) to high (group 10) which implies that J_1^{Adj} consists of the stocks with high downside risk and J_{10}^{Adj} consists of stocks with high upside potential. I 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. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. I 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. I also include the average return ("Avg") for each row and column.

Panel A: β/J^{Adj} Sorted Portfolios

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	Diff	Avg
J_1^{Adj}	0.120	0.148	0.148	0.118	0.153	0.120	0.136	0.144	0.165	0.174	0.055	0.147
J_2^{Adj}	0.127	0.102	0.106	0.102	0.095	0.158	0.179	0.134	0.089	0.225	0.098	0.137
J_3^{Adj}	0.062	0.129	0.100	0.097	0.160	0.135	0.131	0.154	0.062	0.214	0.153	0.128
J_4^{Adj}	0.114	0.115	0.131	0.127	0.154	0.136	0.129	0.143	0.185	0.107	-0.006	0.137
J_5^{Adj}	0.081	0.083	0.151	0.104	0.109	0.186	0.138	0.098	0.120	0.104	0.022	0.122
J_6^{Adj}	0.006	0.110	0.111	0.128	0.139	0.168	0.153	0.122	0.137	0.053	0.046	0.120
J_7^{Adj}	0.041	0.125	0.168	0.124	0.144	0.156	0.157	0.166	0.132	0.046	0.004	0.133
J_8^{Adj}	0.073	0.129	0.144	0.146	0.153	0.142	0.188	0.142	0.115	-0.010	-0.083	0.127
J_9^{Adj}	0.077	0.100	0.149	0.139	0.172	0.120	0.157	0.164	0.113	-0.015	-0.092	0.121
J_{10}^{Adj}	0.129	0.112	0.079	0.158	0.113	0.130	0.158	0.151	0.015	-0.083	-0.213	0.094
Diff	-0.010	0.037	0.069	-0.040	0.039	-0.009	-0.021	-0.007	0.151	0.258		
Avg	0.088	0.116	0.128	0.125	0.139	0.145	0.153	0.142	0.111	0.077		

Panel B: $Cosk/J^{Adj}$ Sorted Portfolios

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	Diff	Avg
J_1^{Adj}	0.158	0.190	0.067	0.113	0.157	0.171	0.131	0.187	0.173	0.158	0.001	0.147
J_2^{Adj}	0.173	0.119	0.096	0.155	0.094	0.133	0.133	0.138	0.195	0.211	-0.038	0.137
J_3^{Adj}	0.126	0.116	0.147	0.154	0.137	0.098	0.100	0.114	0.102	0.180	-0.054	0.128
J_4^{Adj}	0.110	0.169	0.170	0.106	0.113	0.116	0.130	0.100	0.168	0.187	-0.078	0.137
J_5^{Adj}	0.103	0.122	0.110	0.114	0.146	0.120	0.111	0.135	0.127	0.107	-0.004	0.122
J_6^{Adj}	0.099	0.111	0.103	0.099	0.135	0.115	0.163	0.112	0.142	0.122	-0.023	0.120
J_7^{Adj}	0.131	0.093	0.112	0.146	0.129	0.144	0.129	0.154	0.154	0.117	0.015	0.133
J_8^{Adj}	0.123	0.103	0.070	0.138	0.105	0.177	0.131	0.131	0.144	0.119	0.003	0.127
J_9^{Adj}	0.060	0.143	0.123	0.090	0.176	0.155	0.098	0.137	0.090	0.113	-0.053	0.121
J_{10}^{Adj}	0.098	0.152	0.173	0.059	0.167	0.107	0.053	0.041	0.069	0.109	-0.010	0.094
Diff	0.060	0.038	-0.106	0.054	-0.010	0.064	0.078	0.146	0.103	0.049		
Avg	0.131	0.135	0.115	0.119	0.133	0.133	0.116	0.122	0.125	0.127		

Cross-sectional Regressions: J^{Adj} (1992-2013)

Table 4.4: I measure the in-sample risk premia using the Ang, Chen, and Xing (2006a). I also estimate the Fama and MacBeth (1973) intertemporal regression method to generate out-of-sample estimates of the risk premia and 3-month and 6-month predictive regressions estimated every month rolling forward. In the Ang et al. (2006a) regressions, at a given month, t, the average of the next 12 excess monthly returns is regressed against β, β^{-}, β^{+}, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj} estimated using the next 12 months of daily excess return data, and size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret"), computed as at time t. In the Fama and MacBeth (1973) regressions, I use the next one-month monthly excess return as dependent variable, whereas in the predictive regressions I use mean monthly excess return from the next three months, six months, nine months, twelve months and fifteen months. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987b) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994b) automatic lag selection method to determine the lag length. All coefficients are reported as effective annual rates

	In-sample Regressions	Out-of-sample Regressions	Predictive regressions 3m	6m
Int	0.283	0.173	0.208	0.199
	[3.311]	[1.887]	[2.971]	[2.663]
β	-0.025	-0.127	-0.086	-0.062
	[0.619]	[2.035]	[1.960]	[1.253]
Size	-0.016	-0.011	-0.013	-0.013
	[2.578]	[1.583]	[2.669]	[2.320]
BM	0.005	0.025	0.021	0.020
	[0.304]	[1.280]	[1.497]	[1.240]
Past Ret	0.971	1.214	1.836	1.932
	[2.459]	[2.187]	[4.247]	[3.268]
Idio	-1.511	-0.493	-0.111	0.372
	[1.125]	[0.380]	[0.095]	[0.342]
Cosk	0.085	0.167	0.051	0.067
	[1.581]	[1.689]	[0.890]	[1.095]
Cokurt	0.040	0.073	0.053	0.047
	[2.140]	[2.579]	[2.929]	[1.867]
J^{Adj}	-0.004	-0.005	-0.002	-0.001
	[3.642]	[3.287]	[2.455]	[1.023]

Cross-sectional Regressions: $J^{Adj}-$ and $J^{Adj}+$ (1992-2013)

Table 4.5: I measure the in-sample risk premia using the Ang, Chen, and Xing (2006a). I also estimate the Fama and MacBeth (1973) intertemporal regression method to generate out-of-sample estimates of the risk premia and 3-month and 6-month predictive regressions estimated every month rolling forward. In the Ang et al. (2006a) regressions, at a given month, t, the average of the next 12 excess monthly returns is regressed against β, β^{-}, β^{+}, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt"), $J^{Adj}-$ and $J^{Adj}+$ estimated using the next 12 months of daily excess return data, size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret"), computed as at time t. In the Fama and MacBeth (1973) regressions, I use the next one-month monthly excess return as dependent variable, whereas in the predictive regressions I use mean monthly excess return from the next three months, six months, nine months, twelve months and fifteen months. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987b) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994b) automatic lag selection method to determine the lag length. All coefficients are reported as effective annual rates

	In-sample Regressions	Out-of-sample Regressions	Predictive regressions 3m	6m
Int	0.293	0.196	0.228	0.211
	[3.205]	[2.010]	[2.809]	[2.633]
β	-0.021	-0.120	-0.081	-0.060
	[0.526]	[1.940]	[1.630]	[1.206]
Size	-0.016	-0.012	-0.014	-0.014
	[2.543]	[1.691]	[2.515]	[2.372]
BM	0.004	0.023	0.020	0.020
	[0.245]	[1.146]	[1.246]	[1.279]
Past Ret	0.942	1.188	1.820	1.904
	[2.369]	[2.120]	[3.674]	[3.210]
Idio	-1.223	-0.559	-0.074	0.429
	[0.912]	[0.430]	[0.059]	[0.391]
Cosk	0.095	0.159	0.058	0.076
	[1.670]	[1.625]	[0.909]	[1.255]
Cokurt	0.039	0.072	0.051	0.046
	[1.961]	[2.555]	[2.491]	[1.841]
$J^{Adj}-$	-0.003	-0.003	-0.0003	-0.00001
	[2.238]	[1.541]	[0.145]	[0.008]
$J^{Adj}+$	-0.011	-0.017	-0.014	-0.007
	[2.551]	[2.429]	[2.228]	[1.214]

In-sample Regressions: US REITs vs US equities (1992-2013)

Table 4.6: I compare the in-sample risk premia of US REITs estimated using the equally-weighted Ang et al. (2006a) asset pricing regressions with the Alcock and Hatherley (2016) risk premia of US equities estimated using the same Ang et al. (2006a) procedure. The results of the risk premia of US equities refer to Table 3 from Alcock and Hatherley (2016). I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013 and NYSE stocks listed between January 1992 and June 2013 (US industrial equities). Statistical significance is determined using Newey and West (1987b) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994b) 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.

	US REITs				**US equities**			
	I	III	IV	mean (std)	I	III	IV	mean (std)
Int	0.296	0.277	0.293		0.391	0.379	0.388	
	[3.259]	[3.182]	[3.205]		[4.702]	[4.685]	[4.688]	
β	-0.025	-0.027	-0.021	0.640	0.106	0.101	0.104	0.900
	[0.613]	[0.662]	[0.526]	(0.570)	[3.068]	[3.003]	[3.019]	(0.499)
Log-size	-0.016	-0.016	-0.016	12.859	-0.021	-0.021	-0.021	13.981
	[2.570]	[2.501]	[2.543]	(1.752)	[4.345]	[4.346]	[4.354]	(0.441)
BM	0.008	0.006	0.004	0.659	-0.025	-0.025	-0.026	0.605
	[0.454]	[0.366]	[0.245]	(0.552)	[2.050]	[2.074]	[2.079]	(1.688)
Past ret	0.994	1.000	0.942	0.010	-0.071	-0.043	-0.043	0.008
	[2.456]	[2.478]	[2.369]	(0.026)	[0.346]	[0.210]	[0.212]	(0.030)
Idio	-1.086	-1.206	-1.223	0.019	-4.572	-4.629	-4.655	0.021
	[0.814]	[0.897]	[0.912]	(0.014)	[3.835]	[3.895]	[3.907]	(0.011)
Cosk	0.025	0.093	0.095	-0.080	-0.158	-0.049	-0.047	-0.113
	[0.490]	[1.632]	[1.670]	(0.191)	[3.497]	[1.332]	[1.292]	(0.221)
Cokurt	0.037	0.040	0.039	1.746	-0.003	0.002	0.001	2.057
	[1.888]	[2.027]	[1.961]	(1.482)	[0.401]	[0.240]	[0.065]	(1.443)
J^{Adj}		-0.004		-1.576		-0.005		-2.574
		[3.675]		(5.771)		[5.011]		(5.838)
$J^{Adj}-$			-0.003	-5.294			-0.004	-5.659
			[2.238]	(3.003)			[4.280]	(3.257)
$J^{Adj}+$			-0.011	5.074			-0.009	5.225
			[2.551]	(2.793)			[4.667]	(2.926)

$J^{Adj}-$ and $J^{Adj}+$ Average Migration probabilities (1992-2013)

Table 4.7: J^{Adj} is estimated using a 12-month rolling window of daily returns. I calculate probability of migrations between $J^{Adj}-$ and $J^{Adj}+$ using non-overlapping data to account for autocorrelation issues. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013.

	$J^{Adj}-$	$J^{Adj}+$
$J^{Adj}-$	70.953%	29.047%
$J^{Adj}+$	50.135%	49.865%

Structural break test

Table 4.8: I test for a statistical difference in means of β, J^{Adj}, $J^{Adj}-$ and $J^{Adj}+$ in the periods before and after the global financial crisis of 2007/2009. I choose September 2008 to define the "pre-crisis" and "after crisis" period. The statistical significance of the difference in means is tested using the two-sample T-test with unequal standard deviations. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013.

Factor level	β	J^{Adj}	$J^{Adj}-$	$J^{Adj}+$
P-value	< 0.01%	< 0.01%	< 0.01%	< 0.01%
T-stat	-100.989	-17.661	-9.077	16.545
Diff in means	-0.769	-1.412	-0.526	0.978
Mean before 09/2008	0.437	-1.939	-5.410	5.408
Mean after 09/2008	1.206	-0.527	-4.884	4.430
Std before 09/2008	0.418	5.847	2.986	2.863
Std after 09/2008	0.562	5.430	3.032	2.531

Factor sensitivity	β	J^{Adj}	$J^{Adj}-$	$J^{Adj}+$
P-value	< 0.01%	< 0.01%	< 0.01%	19.550%
T-stat	-6.646	-5.444	-4.703	-1.304
Diff in means	-0.223	-0.004	-0.011	-0.002
Mean before 09/2008	-0.082	-0.005	-0.013	-0.003
Mean after 09/2008	0.141	-0.001	-0.002	-0.001
Std before 09/2008	0.234	0.007	0.026	0.010
Std after 09/2008	0.231	0.004	0.011	0.013

Time Variations: In-sample Mean Factor Sensitivity

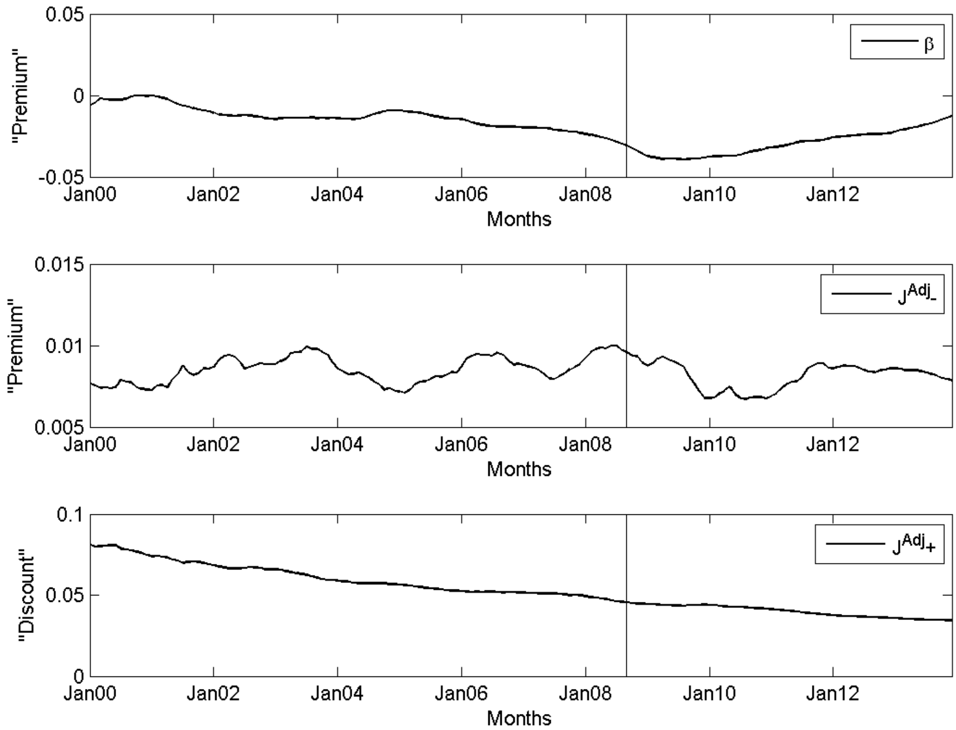


Figure 4.3: This figure depicts the factor sensitivity per unit of standard deviation of given risk factor using the in-sample asset pricing procedure where cross-sectional regressions are computed every month rolling forward. At a given month t, the average of the next 12 excess monthly returns is regressed against β, idiosyncratic risk, J^{Adj}, coskewness and cokurtosis 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. I proxy the market portfolio with the NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorised at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. The Premium for β, Coskewness and Cokurtosis between January 2000 and December 2013 is given by the time series mean factor sensitivity using all historical sensitivity estimates up to and including time t. The vertical line corresponds to the failure of Lehman Brothers in September 2008.

The Time Series Average Returns for Double Sorted Portfolios

Table 4.9: For a given month, I first sort stocks into β^- deciles, and then into J^{Adj} deciles within each characteristic decile in Panel A. In Panel B, I first sort stocks into β^+ deciles and then into J^{Adj} deciles within each characteristic decile. Dependence ranges from low (group 1) to high (group 10) which implies that J_1^{Adj} consists of the stocks with high downside risk and J_{10}^{Adj} consists of stocks with high upside potential. I 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. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. I 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. I also include the average return ("Avg") for each row and column.

Panel A: β^-/J^{Adj} Sorted Portfolios

	β_1^-	β_2^-	β_3^-	β_4^-	β_5^-	β_6^-	β_7^-	β_8^-	β_9^-	β_{10}^-	Diff	Avg
J_1^{Adj}	0.111	0.160	0.143	0.116	0.125	0.104	0.123	0.127	0.155	0.246	0.135	0.147
J_2^{Adj}	0.136	0.142	0.098	0.139	0.100	0.131	0.079	0.125	0.178	0.182	0.047	0.137
J_3^{Adj}	0.064	0.106	0.151	0.117	0.128	0.110	0.164	0.097	0.106	0.209	0.145	0.128
J_4^{Adj}	0.089	0.134	0.127	0.107	0.145	0.146	0.139	0.163	0.173	0.128	0.039	0.137
J_5^{Adj}	0.054	0.139	0.136	0.132	0.144	0.132	0.107	0.118	0.123	0.118	0.064	0.122
J_6^{Adj}	0.065	0.104	0.125	0.139	0.138	0.112	0.147	0.143	0.122	0.078	0.012	0.120
J_7^{Adj}	0.078	0.109	0.144	0.149	0.154	0.123	0.161	0.157	0.097	0.100	0.022	0.133
J_8^{Adj}	0.089	0.165	0.134	0.137	0.149	0.148	0.139	0.153	0.112	0.005	-0.085	0.127
J_9^{Adj}	0.073	0.135	0.154	0.128	0.149	0.101	0.147	0.165	0.086	0.028	-0.045	0.121
J_{10}^{Adj}	0.090	0.133	0.104	0.139	0.099	0.119	0.100	0.098	0.049	-0.060	-0.150	0.094
Diff	0.021	0.027	0.039	-0.023	0.026	-0.015	0.023	0.029	0.106	0.305		
Avg	0.087	0.133	0.133	0.131	0.134	0.123	0.131	0.135	0.122	0.118		

Panel B: β^+/J^{Adj} Sorted Portfolios

	β_1^+	β_2^+	β_3^+	β_4^+	β_5^+	β_6^+	β_7^+	β_8^+	β_9^+	β_{10}^+	Diff	Avg
J_1^{Adj}	0.155	0.119	0.086	0.096	0.168	0.106	0.205	0.178	0.177	0.160	0.006	0.147
J_2^{Adj}	0.110	0.111	0.112	0.132	0.147	0.151	0.135	0.120	0.143	0.186	0.075	0.137
J_3^{Adj}	0.070	0.123	0.118	0.140	0.170	0.113	0.137	0.116	0.088	0.143	0.074	0.128
J_4^{Adj}	0.084	0.114	0.118	0.147	0.123	0.162	0.178	0.153	0.135	0.093	0.009	0.137
J_5^{Adj}	0.055	0.096	0.106	0.102	0.129	0.166	0.146	0.140	0.106	0.115	0.060	0.122
J_6^{Adj}	0.040	0.093	0.114	0.116	0.105	0.149	0.182	0.142	0.134	0.079	0.038	0.120
J_7^{Adj}	0.093	0.116	0.115	0.143	0.122	0.127	0.178	0.137	0.104	0.105	0.011	0.133
J_8^{Adj}	0.066	0.154	0.162	0.120	0.140	0.159	0.144	0.155	0.110	0.024	-0.042	0.127
J_9^{Adj}	0.089	0.173	0.150	0.126	0.144	0.124	0.116	0.155	0.101	0.055	-0.034	0.121
J_{10}^{Adj}	0.148	0.062	0.102	0.176	0.117	0.086	0.134	0.110	0.095	-0.047	-0.195	0.094
Diff	0.007	0.058	-0.016	-0.080	0.051	0.020	0.070	0.068	0.082	0.208		
Avg	0.098	0.115	0.116	0.130	0.135	0.136	0.154	0.140	0.115	0.077		

Alternative downside risk measure: β^- (1992-2013)

Table 4.10: I measure the in-sample risk premia using the Ang, Chen, and Xing (2006a) where cross-sectional regressions are computed every month rolling forward. At a given month, t, the average of the next 12 excess monthly returns is regressed against β, β^-, β^+, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj} estimated using the next 12 months of daily excess return data, $J^{Adj}-$, $J^{Adj}+$, size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret"), computed as at time t. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987a) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994a) automatic lag selection method to determine the lag length. The mean and standard deviation (in parentheses) for each variable is provided at the last column. All coefficients are reported as effective annual rates.

	I	II	III
Int	0.299	0.280	3.411
	[3.451]	[3.411]	[0.294]
β^-	0.0327	0.045	1.140
	[0.851]	[1.140]	[0.047]
β^+	-0.0358	-0.047	-1.484
	[1.169]	[1.484]	[0.047]
Log-size	-0.017	-0.016	-2.674
	[2.742]	[2.674]	[0.016]
BM	0.008	0.007	0.420
	[0.461]	[0.420]	[0.005]
Past ret	1.092	1.093	2.673
	[2.661]	[2.673]	[1.051]
Idio	-1.716	-1.872	-1.390
	[1.299]	[1.390]	[1.892]
Cosk	0.156	0.267	2.147
	[1.478]	[2.147]	[0.271]
Cokurt	0.037	0.043	2.281
	[2.078]	[2.281]	[0.044]
J^{Adj}		-0.004	
		[3.756]	
$J^{Adj}-$			-0.003
			[2.183]
$J^{Adj}+$			-0.013
			[2.729]

Equally-weighted In-sample Regressions (1992-2013)

Table 4.11: I measure the in-sample risk premia using the Ang, Chen, and Xing (2006a) where cross-sectional regressions are computed every month rolling forward. At a given month, t, the average of the next 12 excess monthly returns is regressed against β, β^{-}, β^{+}, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj} estimated using the next 12 months of daily excess return data, and size ("Log-size"), book-to-market ratio ("BM") and the average past 12-monthly excess return ("Past Ret"), computed as at time t. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987a) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994a) automatic lag selection method to determine the lag length. The mean and standard deviation (in parentheses) for each variable is provided at the last column. All coefficients are reported as effective annual rates.

	I	II	III	IV	V	mean (std)
Int	0.296	0.105	0.277	0.293	0.293	
	[3.259]	[3.784]	[3.182]	[3.205]	[3.353]	
β	-0.025		-0.027	-0.021		0.640
	[0.613]		[0.662]	[0.526]		(0.570)
β^{-}		0.007			0.050	0.677
		[0.213]			[1.256]	(0.571)
β^{+}		-0.009			-0.048	0.627
		[0.396]			[1.519]	(0.671)
Log-size	-0.016		-0.016	-0.016	-0.016	12.859
	[2.570]		[2.501]	[2.543]	[2.643]	(1.752)
BM	0.008		0.006	0.004	0.006	0.659
	[0.454]		[0.366]	[0.245]	[0.382]	(0.552)
Past ret	0.994		1.000	0.942	1.061	0.010
	[2.456]		[2.478]	[2.369]	[2.584]	(0.026)
Idio	-1.086		-1.206	-1.223	-1.739	0.019
	[0.814]		[0.897]	[0.912]	[1.276]	(0.014)
Cosk	0.025		0.093	0.095	0.281	-0.080
	[0.490]		[1.632]	[1.670]	[2.258]	(0.191)
Cokurt	0.037		0.040	0.039	0.044	1.746
	[1.888]		[2.027]	[1.961]	[2.269]	(1.482)
J^{Adj}			-0.004			-1.576
			[3.675]			(5.771)
$J^{Adj}-$				-0.003	-0.003	-5.294
				[2.238]	[2.353]	(3.003)
$J^{Adj}+$				-0.0114	-0.013	5.074
				[2.551]	[2.715]	(2.793)

Out-of-sample Regression Specifications (1992-2013)

Table 4.12: I measure the out-of-sample 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 next excess monthly return is regressed against β, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt"), $J^{Adj}-$ and $J^{Adj}+$ estimated using the past 12 months of daily excess return data. I 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. I provide regression results using all available observations, as well as a series of regressions excluding the top quintile, top decile and top vigintile of volatile stocks, where volatility is measured as the standard deviation of the past 12 months of daily excess returns. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987a) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994a) 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 (Std)
Int	0.202	0.209		0.210	0.217		0.208	0.215		0.208	0.215	
	[2.167]	[2.151]		[2.379]	[2.370]		[2.353]	[2.347]		[2.353]	[2.347]	
β	-0.125	-0.115	0.739	-0.093	-0.083	0.625	-0.094	-0.0832	0.625	-0.094	-0.083	0.625
	[2.030]	[1.895]	(0.481)	[1.475]	[1.328]	(0.541)	[1.485]	[1.338]	(0.541)	[1.485]	[1.338]	(0.541)
Log-size	-0.012	-0.012	13.439	-0.013	-0.012	12.852	-0.013	-0.012	12.852	-0.013	-0.012	12.852
	[1.892]	[1.816]	(0.406)	[2.001]	[1.888]	(0.518)	[1.984]	[1.874]	(0.519)	[1.984]	[1.874]	(0.519)
BM	0.024	0.023	0.691	0.026	0.024	0.680	0.027	0.025	0.680	0.027	0.025	0.680
	[1.248]	[1.177]	(1.139)	[1.304]	[1.212]	(1.743)	[1.339]	[1.245]	(1.743)	[1.339]	[1.245]	(1.743)
Past ret	1.368	1.307	0.009	1.586	1.542	0.009	1.568	1.525	0.009	1.568	1.525	0.009
	[2.467]	[2.316]	(0.022)	[2.704]	[2.587]	(0.025)	[2.675]	[2.561]	(0.025)	[2.675]	[2.561]	(0.025)
Idio	-0.611	-0.901	0.020	-1.079	-1.392	0.020	-1.061	-1.372	0.020	-1.061	-1.372	0.020
	[0.453]	[0.668]	(0.010)	[0.818]	[1.051]	(0.013)	[0.805]	[1.038]	(0.013)	[0.805]	[1.038]	(0.013)
Cosk	0.084	0.195	-0.087	0.076	0.198	-0.087	0.076	0.198	-0.087	0.076	0.198	-0.087
	[0.885]	[1.916]	(0.187)	[0.856]	[2.053]	(0.210)	[0.859]	[2.054]	(0.210)	[0.859]	[2.054]	(0.210)
Cokurt	0.073	0.072	1.705	0.058	0.054	1.705	0.058	0.055	1.705	0.058	0.055	1.705
	[2.679]	[2.663]	(1.432)	[2.179]	[2.092]	(1.666)	[2.187]	[2.100]	(1.666)	[2.187]	[2.100]	(1.666)
$J^{Adj}-$		-0.004	-5.200		-0.004	-5.200		-0.004	-5.200		-0.004	-5.200
		[1.764]	(2.439)		[2.093]	(2.947)		[2.088]	(2.946)		[2.088]	(2.946)
$J^{Adj}+$		-0.018	5.012		-0.018	5.012		-0.018	5.012		-0.018	5.012
		[2.678]	(2.559)		[2.719]	(2.769)		[2.718]	(2.769)		[2.718]	(2.769)

In-sample Alternative Regression Specifications (1992-2013)

Table 4.13: I measure the in-sample risk premia using the Ang, Chen, and Xing (2006a) where equally-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 β, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj}. I 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. I provide regression results using daily, weekly and fortnightly data with six months to five years of rolling windows. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987a) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994a) automatic lag selection method to determine the lag length. The mean and standard deviation (in parentheses) for each variable is provided. All coefficients are reported as effective annual rates.

	daily 6m		mean	daily 24m		mean	daily 60m		mean	weekly 5yr		mean	fortnightly 5yr		mean
	I	III	(std)	I	III	(std)	I	III	(std)	I	III	(std)	I	III	(std)
Int	0.164	0.159		0.082	0.073		0.234	0.220		0.004	-0.004		-0.015	-0.034	
	[3.826]	[3.773]		[2.179]	[1.958]		[4.584]	[4.479]		[0.309]	[0.316]		[0.425]	[0.939]	
β	0.007	0.006	0.630	-0.061	-0.061	0.642	0.004	0.001	0.687	-0.034	-0.041	0.734	0.028	0.021	0.721
	[0.243]	[0.201]	(0.594)	[1.174]	[1.200]	(0.569)	[0.123]	[0.019]	(0.620)	[0.958]	[1.113]	(0.670)	[0.669]	[0.445]	(0.684)
Log-size	-0.006	-0.006	10.502	-0.002	-0.001	10.668	-0.008	-0.008	12.120	0.000	0.000	9.917	0.002	0.002	10.585
	[3.873]	[3.858]	(5.712)	[0.943]	[0.702]	(5.621)	[3.125]	[3.041]	(3.284)	[0.309]	[0.357]	(6.073)	[1.332]	[1.345]	(5.704)
BM	0.005	0.005	0.669	0.005	0.004	0.659	0.029	0.028	0.628	-0.032	-0.029	0.636	-0.100	-0.101	0.617
	[0.318]	[0.326]	(0.586)	[0.306]	[0.238]	(0.552)	[3.143]	[3.037]	(0.726)	[3.060]	[2.969]	(0.506)	[3.481]	[3.491]	(0.436)
Past ret	0.876	0.899	0.010	1.122	1.098	0.010	-0.606	-0.593	0.009	2.116	2.247	0.003	0.051	0.063	0.026
	[2.246]	[2.295]	(0.026)	[2.751]	[2.723]	(0.026)	[2.430]	[2.399]	(0.024)	[1.782]	[1.879]	(0.006)	[0.195]	[0.242]	(0.046)
Idio	-2.093	-2.101	0.019	0.410	0.462	0.020	-1.081	-1.130	0.021	4.657	4.629	0.046	7.040	7.066	0.061
	[1.573]	[1.559]	(0.015)	[0.345]	[0.391]	(0.013)	[1.491]	[1.559]	(0.013)	[4.556]	[4.566]	(0.028)	[4.471]	[4.465]	(0.039)
Cosk	-0.001	0.025	-0.074	0.068	0.123	-0.088	0.058	0.112	-0.064	-0.014	0.015	-0.035	0.011	0.083	-0.051
	[0.045]	[0.779]	(0.242)	[1.315]	[1.968]	(0.159)	[1.368]	[2.183]	(0.128)	[0.380]	[0.380]	(0.241)	[0.261]	[1.677]	(0.355)
Cokurt	0.030	0.030	1.481	0.038	0.039	2.079	0.004	0.007	2.583	0.014	0.018	2.383	0.021	0.032	2.448
	[1.906]	[1.979]	(1.340)	[1.928]	[1.954]	(1.808)	[0.413]	[0.576]	(2.343)	[1.489]	[1.763]	(2.098)	[1.329]	[1.843]	(2.407)
J^{Adj}		-0.002	-1.442		-0.002	-1.969		-0.003	-2.229		-0.002	-3.004		-0.004	-3.256
		[2.447]	(6.537)		[2.400]	(5.810)		[3.728]	(6.221)		[2.874]	(4.800)		[2.653]	(5.657)

Out-of-sample Alternative Regression Specifications (1992-2013)

Table 4.14: I measure the out-of-sample risk premia using the Fama and MacBeth (1973) 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 excess monthly return is regressed against β, idiosyncratic risk ("Idio"), coskewness ("Cosk"), cokurtosis ("Cokurt") and J^{Adj}. I 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. I provide regression results using daily, weekly and fortnightly data with six months to five years of rolling windows. I proxy the market portfolio with the CRSP Value Weighted return of all NYSE, AMEX and NASDAQ stocks and the risk free rate with the 1 month T-bill rate. All regressors are Winsorized at the 1% and 99% level at each month. I restrict my attention to REIT stocks listed on the NYSE between January 1992 and December 2013. Statistical significance is determined using Newey and West (1987a) adjusted t-statistics, given in parentheses, to control for overlapping data using the Newey and West (1994a) automatic lag selection method to determine the lag length. The mean and standard deviation (in parentheses) for each variable is provided. All coefficients are reported as effective annual rates.

	daily 6m		mean	daily 24m		mean	daily 60m		mean	weekly 5yr		mean	fortnightly 5yr		mean
	I	III	(std)	I	III	(std)	I	III	(std)	I	III	(std)	I	III	(std)
Int	-0.022	-0.025		-0.005	-0.004		0.234	0.220		0.002	-0.006		-0.010	-0.026	
	[0.793]	[0.896]		[0.560]	[0.473]		[4.584]	[4.479]		[0.187]	[0.483]		[0.332]	[0.857]	
β	-0.056	-0.055	0.629	-0.016	-0.015	0.642	0.004	0.001	0.687	-0.032	-0.037	0.723	0.032	0.023	0.721
	[1.904]	[1.859]	(0.594)	[1.379]	[1.314]	(0.570)	[0.123]	[0.019]	(0.620)	[1.034]	[1.169]	(0.664)	[0.774]	[0.523]	(0.684)
Log-size	0.000	0.000	10.506	0.000	0.000	10.674	-0.008	-0.008	12.120	0.000	0.001	9.724	0.001	0.001	10.585
	[0.143]	[0.124]	(5.708)	[0.768]	[0.815]	(5.616)	[3.125]	[3.041]	(3.284)	[0.603]	[0.672]	(6.155)	[0.930]	[0.944]	(5.704)
BM	0.005	0.005	0.669	0.004	0.004	0.661	0.029	0.028	0.628	-0.028	-0.026	0.639	-0.093	-0.094	0.617
	[0.616]	[0.635]	(0.586)	[1.574]	[1.545]	(0.549)	[3.143]	[3.037]	(0.726)	[2.930]	[2.823]	(0.528)	[3.460]	[3.462]	(0.436)
Past ret	6.406	6.375	0.010	10.965	10.954	0.010	-0.606	-0.593	0.009	1.669	1.758	0.003	0.027	0.039	0.026
	[5.038]	[5.039]	(0.026)	[5.059]	[5.059]	(0.026)	[2.430]	[2.399]	(0.024)	[1.584]	[1.650]	(0.006)	[0.105]	[0.154]	(0.046)
Idio	2.090	2.028	0.019	0.439	0.407	0.020	-1.081	-1.130	0.021	4.332	4.304	0.046	6.619	6.638	0.061
	[2.503]	[2.467]	(0.014)	[1.665]	[1.559]	(0.013)	[1.491]	[1.559]	(0.013)	[4.912]	[4.921]	(0.028)	[4.521]	[4.515]	(0.039)
Cosk	-0.022	0.015	-0.073	0.017	0.029	-0.089	0.058	0.112	-0.064	-0.022	0.005	-0.035	-0.010	0.054	-0.051
	[0.625]	[0.403]	(0.242)	[1.426]	[2.215]	(0.159)	[1.368]	[2.183]	(0.128)	[0.662]	[0.129]	(0.238)	[0.248]	[1.232]	(0.355)
Cokurt	0.036	0.036	1.483	0.007	0.007	2.081	0.004	0.007	2.583	0.009	0.012	2.331	0.018	0.028	2.448
	[2.173]	[2.224]	(1.343)	[1.882]	[1.921]	(1.810)	[0.413]	[0.576]	(2.343)	[1.363]	[1.617]	(2.087)	[1.235]	[1.688]	(2.407)
J^{Adj}		-0.002	-1.440		-0.0004	-1.965		-0.003	-2.229		-0.002	-3.037		-0.003	-3.256
		[3.212]	(6.538)		[2.039]	(5.805)		[3.728]	(6.221)		[2.942]	(4.835)		[2.374]	(5.657)

5

Heterogeneous Cash-flow Risk, Preference Shocks and Asymmetric Return Dependence

5.1 Introduction

I show that heterogeneous cash-flow risk explains the cross section of the firm-level asymmetric dependence. The fundamental cash-flow risk is measured using the covariance between firm cash-flow growth and aggregate consumption growth (Menzly et al., 2004). I build an equilibrium model of the economy where investors experience preference shocks correlated with the business cycle and trade multiple risky assets, and whose future cash flows are affected by heterogeneous cash-flow risks of firms. The existence of preference shocks is consistent with investors being more sensitive to changes in utility levels during bad times. Asymmetric dependence between stock returns and market returns emerges when the effect of investor preference shocks interacts with the firm-level cash-flow risk. The proposed model generates moments that are able to match important characteristics of asset prices.

The existence of preference shocks is crucial in understanding the behavior of equity premia. Consider, for example, the impact of a serious economic downturn in the economy; firms pay low dividends, investors experience low consumption levels, and also realize a high preference shock. The effect of the preference shock makes investors value even more each additional unit of consumption, because their marginal utility depends positively on preference shocks. As a result, the existence of preference shocks increases the discount rate that investors use to price risky assets, which further increases anticipated excess returns for a given level of risk aversion.

In the proposed model, preference shocks lead to time-varying and state-dependent asset prices. Investors are particularly sensitive to consuming less during bad times and any shock to individual consumption is thus more painful during economic downturns. The cash-flow dynamics of the risky assets in the economy are affected by heterogeneous cash-flow risks. Risky assets differ in their cash-flow growth reactions to economic shocks. Firms from various industries may experience differing demand reactions from consumers following a negative shock to the economy, which generates heterogeneous cash-flow risks of firms.

The sign and the magnitude of the cash-flow risk determine whether a risky asset is a good or a bad hedge against negative consumption shocks (Menzly et al., 2004). If the covariance is negative, asset cash flows grow faster in the presence of any decrease in aggregate consumption growth. Consequently, these assets will serve as natural hedges against negative consumption shocks and may also perform relatively better than other assets during bad times.

To understand the intuition of the model, consider first a bear market scenario. During market downturns, negative shocks to aggregate consumption decrease the current personal consumption of individual agents. This automatically leads to a drop in investor utility and an increase in risk aversion. Investors shift their attention to safe assets and prefer to sell risky assets. This change in demand for risky assets is not proportional, however. Agents prefer to sell assets with the worst performance first. High cash-flow risk stocks that exhibit a high covariance of cash-flow growth with consumption growth are likely to perform relatively worse. As a result, the dependence of high cash-flow risk stocks on market returns is higher relative to low cash-flow risk stocks. In addition, agents experience a positive preference shock in depressed economic conditions and the total effect of negative consumption shocks on asset prices is thus magnified.

Conversely, during market upturns the individual consumption and utility of agents increase. Investors increase their demand for risky assets, particularly for high-cash flow risk assets that experience a relatively high increase in cash-flow growth. Nevertheless, the total effect of the increased demand for high cash-flow risk stocks is lower due to the presence of a negative preference shock experienced during market upturn periods. Consequently, the effect of heterogeneous cash-flow risk of firms on the conditional return dependence is stronger during bad times relative to good times. This mechanism generates asymmetric dependence between stock and market returns in the economy.

In this paper, I show within a general equilibrium model that conditional dependence measures (conditional β) and the degree of asymmetric dependence are associated with the firm level of fundamental cash-flow risk. Assets with a high cash-flow covariance risk do not only have higher unconditional consumption βs. I demonstrate that high cash-flow risk stocks also exhibit higher degrees of asymmetric dependence and time variation in conditional dependence measures. The proposed model suggests that stocks with a high fundamental cash-flow risk are likely to perform relatively poorly during market downturns.

Asymmetric dependence of asset returns is generated by the interaction between heterogeneous cash-flow risks of firms and preference shocks experienced by investors. Both of these two components of the model are relevant to capture the cross section of asset prices and their conditional moments. Without the preference shocks, the model is unable to generate a sufficient amount of time variation that is observed in financial markets. Without heterogeneous cash-flow risks, all assets would behave and perform in the same manner. This paper contributes to the existing literature by noting the importance of preference shocks for equilibrium asset pricing and providing a theoretical link between the firm level of cash-flow risk and conditional asymmetric dependence measures.

I test the model implications using a variety of empirical proxies of aggregate consumption shocks. I find that heterogeneous cash-flow risk affects the asset's conditional dependence structure. I also show that US industries with high cash-flow risk have a higher degree of asymmetric dependence. These empirical results confirm the model predictions suggesting that assets with a high covariance of cash-flow and consumption growth will perform relatively poorly during market downturns. I conclude that firms with a high cash-flow risk experience abnormal losses in market downturns that are driven by the asymmetric dependence of stock returns.

This paper extends our understanding of the cross-sectional drivers of asymmetric return dependence. This work is closely related to Santos and Veronesi (2004), who examine the effects of cash-flow risk on conditional betas using a habit formation model introduced by Campbell and Cochrane (1999). Although closely related, this paper differs from Santos and Veronesi (2004) in a number of ways, firstly through the use of preference shocks to explain time variation of asset prices rather than external habits. In particular, I explain how the existence of preference shocks generates the state dependence of asset prices. Secondly, this paper shows in a closed form how fundamental cash-flow risks drive asymmetric return dependence. Third, it confirms the model predictions using various empirical tests and measures of firm cash-flow risks using US industry data.

The remainder of this paper is structured as follows. Section 5.2 presents the theoretical model, Section 5.3 describes the predictions of the model. Section 5.4 describes the data used. Section 5.5 tests the theoretical implications and Section 5.6 concludes.

5.2 The Model

Aggregate Economy

The aggregate consumption dynamics follow a geometric process with a time-varying consumption volatility. Specifically,

$$\frac{dC_t}{C_t} = \mu_C dt + \sigma_C(Y_t) dZ_t^1, \tag{5.1}$$

where μ_C is the expected value of consumption growth, $\sigma_C(Y_t)$ is the volatility of aggregate consumption, and dZ_t^1 is a (1×1) Brownian motion. The volatility of consumption growth ($\sigma_C(Y_t)$) depends on the state variable Y_t. I follow Santos and Veronesi (2017) and assume that the consumption growth volatility is countercyclical and positively related to the recession indicator Y_t.

$$\sigma_C(Y_t) = \sigma_{max}(1 - \lambda/Y_t) \tag{5.2}$$

The state variable Y_t represents a recession indicator. This means that the value of Y_t is high during recessions and low during market booms. The dynamics of the state variable Y_t are mean-reverting and correlated with innovations in the aggregate consumption growth.

$$dY_t = k(\bar{Y} - Y_t)dt - vY_t \left[\frac{dC_t}{C_t} - \mu_C dt \right], \tag{5.3}$$

where k is the speed of mean reversion, $\bar{Y}$ is the long run mean of Y_t and the parameter v describes the effects of unexpected consumption shocks on the state variable Y_t. The parameter v is positive, $v > 0$, which implies that with a negative aggregate shock to economy, the value of Y_t increases, and vice versa.

Utility with Preference Shocks

Agents derive utility from individual consumption (C_t^i) and the level of preference shock described by g_t. That is, for agent $i \in \{1, ..., M\}$, the utility function is given by

$$U(C_t^i, g_t, t) = E_t \left[\int_t^{\infty} e^{-\rho(\tau - t)} u_i(C_\tau^i, g_\tau) d\tau \right], \tag{5.4}$$

where $\rho > 0$ is the subjective discount rate and C_t^i is the agent i's consumption rate at time t. The agent i's individual instantaneous utility function is defined as

$$u_i\left(C_t^i, g_t\right) = g_t \log\left(C_t^i\right). \tag{5.5}$$

The preference shock g_t is driven by the current value of the state variable Y_t

$$g_t = a\left(Y_t - \bar{Y}\right) + 1, \tag{5.6}$$

where $\bar{Y}$ is the long-term mean of Y_t and $a > 0$ represents agent sensitivity to preference shocks. The presence of preference shocks suggests that agents' sensitivity to utility shocks depends on market conditions. Moreover, I assume that $a > 0$, which implies that agents are particularly sensitive to any shock to their personal consumption during times of economic downturn.[1] This is because the agent marginal utility will be high when g_t is high, which occurs when Y_t is high and exceeds its long-term level $\bar{Y}$. If, on the other hand, the current value of the state variable Y_t is lower than its long-term level $\bar{Y}$, agents are relatively less concerned with shocks to personal consumption levels and their marginal utility level is relatively low.

The existing literature has explored the effects of preference shocks on asset prices using the framework of the Epstein and Zin (1991) non-separable pref-

[1]The value of the sensitivity parameter a is further restricted so that $a\left(Y_t - \bar{Y}\right) + 1 > 0$ is always satisfied.

erences. Normandin and St-Amour (1998) show that preference shocks statistically influence the equity premia and conclude that preference shocks can be interpreted as proxies for omitted variables characterizing the state dependence of investor preferences. Basu and Bundick (2017) suggest that unlike standard general-equilibrium models, models with preference shocks can easily generate comovement explaining declines in output, consumption, investment, and hours worked, experiences during contraction periods.

The Social Planner's Optimization Problem

Markets are complete and the social planner solves the problem

$$U(C_t, g_t, t) = \max_{C_t^i} \int_I \psi^i U(C_t^i, Y_t, t)di \tag{5.7}$$

subject to $\int_I C_t^i di = C_t$, where $\int_I \psi^i di = 1$.

Proposition 1. *The marginal utility of the representative agent is given by*

$$M_t = e^{-\rho t} C_t^{-1} g_t = e^{-\rho t} C_t^{-1} (a \left(Y_t - \bar{Y}\right) + 1). \tag{5.8}$$

The marginal utility of the representative agent is high during recession periods when g_t is high. The pricing functions follow from the marginal rate of substitution.

$$\frac{M_\tau}{M_t} = \frac{u_C(C_\tau, Y_\tau)}{u_C(C_t, Y_t)} = e^{-\rho(\tau - t)} \frac{C_\tau^{-1}}{C_t^{-1}} \frac{(a\left(Y_\tau - \bar{Y}\right) + 1)}{(a\left(Y_t - \bar{Y}\right) + 1)}. \tag{5.9}$$

Proposition 2. *The price of the claim on the aggregate consumption is given in equilibrium by*

$$\begin{aligned} P_t(C_t, Y_t) &= \mathrm{E}_t \left[\int_t^\infty \frac{M_\tau}{M_t} C_\tau d\tau \right] \\ &= C_t g_t^{-1} \left[\frac{a(Y_t - \bar{Y})}{\rho + k} + \frac{1}{\rho} \right]. \end{aligned} \tag{5.10}$$

The price of the claim on aggregate consumption can be considered as the price of market portfolio. When $a = 0$, the equilibrium price of the claim on aggregate consumption transforms to $P_t = \frac{C_t}{\rho}$. With the existence of preference shocks, i.e. when $a > 0$, the price of the aggregate market portfolio is affected by current market conditions. The price of market portfolio will be high during market upturns when the recession indicator Y_t is low and vice versa. This holds because $\frac{\partial P_t}{\partial Y_t} = C_t \frac{(1-1/\rho)}{g_t^2} < 0$.

Proposition 3. *The equilibrium risk-free rate (r_t) is given by*

$$r_t(Y_t) = \underbrace{\rho + \mu_C}_{(1)} + \underbrace{ak\frac{Y_t}{g_t}(1 - \bar{Y}/Y_t)}_{(2)} - \underbrace{\left(1 + av\frac{Y_t}{g_t}\right)\sigma_C^2(Y_t)}_{(3)}. \tag{5.11}$$

and the market price of risk (σ_M) is in equilibrium equal to

$$\sigma_M(Y_t) = \left(1 + av\frac{Y_t}{g_t}\right)\sigma_C(Y_t). \tag{5.12}$$

The equilibrium risk-free rate can be decomposed into three elements, (1,2,3) from equation (5.50). Without preference shocks, i.e. when $a = 0$, the risk-free rate is constant and fully determined by the discount rate ρ and the consumption growth rate μ_C. In the presence of preference shocks, when $a > 0$, the risk-free rate becomes stochastic and dependent on the market conditions represented by the recession indicator Y_t.

The effect of the market state is described and quantified by terms (2) and (3) from equation (5.50). (2) comes from the mean-reversion dynamics of the state variable Y_t and implies that interest rates will be low during recession periods (when $Y_t > \bar{Y}$) and high in expansions (when $Y_t < \bar{Y}$). (3) is a result of the interaction of the consumption dynamics with the state variable dynamics. Consequently, the equilibrium risk-free rate is low in periods with a high consumption volatility, which occurs during market downturns.

Proposition 4. *The equilibrium volatility of the market portfolio ($\sigma_P(Y_t)$) is given by*

$$\sigma_R(Y_t) = \left(1 + \frac{aY_t}{g_t}\frac{kv}{(\rho a(Y_t - \bar{Y}) + \rho + k)}\right)\sigma_C(Y_t). \tag{5.13}$$

The presence of preference shocks ($a > 0$) creates time-varying volatility of market returns. The magnitude of the time variation is largely affected by the current market conditions (Y_t), and further depends on the sensitivity parameter (a), the speed of mean reversion of the economic state (k) and the discount rate (ρ).

Proposition 5. *The market risk premium at time t, r_t^m, is given by*

$$\begin{aligned} r_t^m(Y_t) &= \mathrm{E}_t(dR_P - r_t dt) \\ &= \sigma_M(Y_t)\sigma_R(Y_t)dt \\ &= \left(1 + av\frac{Y_t}{g_t}\right)\left(1 + \frac{aY_t}{g_t}\frac{kv}{(\rho a(Y_t - \bar{Y}) + \rho + k)}\right)\sigma_C^2(Y_t), \end{aligned} \tag{5.14}$$

where dR_P is the total return on the market portfolio, $dR_P = (dP_t + D_t dt)P_t$.

The market risk premium is time-varying due to the interaction between the dynamics of the state variable Y_t and the aggregate consumption C_t. The market risk premium is positively related to the recession indicator and the sensitivity parameter a.

The Cross Section of Assets

There are N risky assets and one risk-free asset in the economy, each risky asset j pays dividends D_t^j at time t that exist in a form of a perishable consumption good. The dividend payments form agents' aggregate output. Instead of modelling the dividend rate processes, I focus on the share of output that each risky security produces (s_t^j) (Menzly et al., 2004; Santos and Veronesi, 2017).

$$s_t^j = \frac{D_t^j}{C_t}, \text{ for } j = 1, ..., N. \tag{5.15}$$

I also consider other sources of non-dividend income, for example from labor described by s_t^0: $s_t^0 = 1 - \sum_{j=1}^N s_t^j$. The dividend share process of asset j is stationary and mean-reverting.

$$ds_t^j = \phi^j(\bar{s}^j - s_t^j)dt + s_t^j \sigma^j(s_t) dZ_t^n, \tag{5.16}$$

where $\sigma^j(s_t) = (\sigma(s^1), ..., \sigma(s^N))$ is a vector of volatilities,

$$\sigma^j(s_t) = v_j - \sum_{k=1}^{N} s_k(t) v_k, \tag{5.17}$$

ϕ^j is the speed of mean reversion of the share process j, v_i denotes a vector of constants, $v_i = (v_i^1, ..., v_i^n)$ and Z_t^n is a $(n \times 1)$ vector of Brownian motions with $n \leq N+1$. I follow Menzly et al. (2004) and normalize the constants v_i to satisfy $\sum_{k=1}^N \bar{s}_k v_k = 0$, which does not change the share process but simplifies the model derivations. I further assume that the total income equals agents' consumption, $\sum_{k=0}^N s_t^k = 1$, and no individual asset can dominate the consumption, which implies that conditions $\sum_{j=1} \bar{s}^j < 1$ and $\phi^j > \sum_{j=1}^N \bar{s}^j \phi^j$ must be met.

Heterogeneous Cash-Flow Risk

Risky assets exhibit heterogeneous cash-flow risk, where cash-flow risk is the covariance between the growth of the share of dividend output each asset produced (s_t^j) and the growth of aggregate consumption (C_t). This definition follows Menzly et al. (2004). The cash-flow risk of asset j is given by

$$\text{cov}_t\left(\frac{ds_t^j}{s_t^j}, \frac{dC_t}{C_t}\right) = \theta_{CF}^j - \sum_{l=1}^{N} \theta_{CF}^l s_t^l. \tag{5.18}$$

The constants from the vector $\mathbf{v} = (v_1, ..., v_N)$ from equation (5.17) are normalized so that $\text{E}_t\left(\text{cov}_t\left(\frac{ds_t^j}{s_t^j}, \frac{dC_t}{C_t}\right)\right) = \text{E}_t(\sigma^j(s_t)\sigma_C(Y_t)) = \theta_{CF}^j$.

Price Dynamics

The price of the risky asset j is the present value of the expected future dividend income.

$$P_t^j = \mathrm{E}_t\left[\int_t^{\infty} \frac{M_\tau}{M_t} D_\tau^j d\tau\right] \tag{5.19}$$

Using the marginal rate of substitution from (5.9), the price of the risky asset j can be arranged into

$$\begin{aligned} P_t^j &= \int_t^{\infty} \mathrm{E}_t\left(e^{-\rho(\tau-t)} \frac{C_\tau^{-1}}{C_t^{-1}} \frac{g_\tau}{g_t} D_\tau^j\right) d\tau \\ &= C_t g_t^{-1} \int_t^{\infty} e^{-\rho(\tau-t)}\ \mathrm{E}_t\left(g_\tau s_\tau^j\right) d\tau \\ &= C_t g_t^{-1} \int_t^{\infty} e^{-\rho(\tau-t)}\ \mathrm{E}_t\left(q_\tau^j\right) d\tau, \end{aligned} \tag{5.20}$$

where $q_\tau^j = g_\tau s_\tau^j$. I identify the main risk drivers from the cash-flow dynamics by applying the Itô's lemma to q_t^j

$$\begin{aligned} dq_t^j = q_t^j &\left[\underbrace{ak\frac{Y_t}{g_t}\left(\frac{\bar{Y}-Y_t}{Y_t}\right)}_{(1)} + \underbrace{\phi^j \frac{\bar{s}^j - s_t^j}{s_t^j}}_{(2)} \underbrace{-av\sigma_C(Y_t)\sigma^j(s_t)}_{(3)}\right] dt \\ &+ q_t^j \left[\sigma_j(s_t) - av\frac{Y_t}{g_t}\sigma_C(Y_t)\right] dZ_t^N. \end{aligned} \tag{5.21}$$

The drift term from the cash-flow dynamics described in equation (5.21) can be decomposed into three risk drivers. The first risk driver (1) describes the effect of economic conditions on asset prices. The risk driver (1) affects prices through the mean reversion of the state variable Y_t. If the current value of the recession indicator Y_t is below its long-term average $\bar{Y}$, the change in q_t^j increases. The risk driver (2) is generated by the mean reversion of the consumption share dynamics that affect asset prices and expected returns. If the consumption share of the risky asset j is lower than its long-term average, the dividend share s_t^j is expected to rise, which increases the change in the expected cash-flow dynamics ($\uparrow dq_t^j$).

Lastly and most importantly, the heterogeneous cash-flow risk affects cash-flow dynamics and therefore also prices through term (3). The risk driver (3) demonstrates how the covariance between consumption growth and consumption share of the risky assets affects asset prices. Although all aspects of the proposed model are considered, this risk driver is given the most attention in this paper.

In order to derive the price of the risky asset j, one must first derive the value of $\int_t^\infty e^{-\rho(\tau-t)}\, \mathrm{E}_t\left(q_\tau^j\right)$. I follow the method used by Menzly et al. (2004) to find the solution to the stochastic SDE that drives q_t^j to derive the price of the risky assets in the economy (see the proof of Proposition 6 in the Appendix).

Proposition 6. *The price of the risky asset j is given in equilibrium by*

$$P_t^j(Y_t, s_t^j) = C_t g_t^{-1}(\zeta_0^j + \zeta_1^j s_t^j + \zeta_2^j s_t^j Y_t + \zeta_3^j Y_t), \tag{5.22}$$

where

$$\begin{aligned}\zeta_0^j = {} & \frac{a\phi^j \bar{s}^j \bar{Y} k}{\alpha_0}\left[\frac{1}{\phi^j} - \frac{1}{k} + \frac{1}{\phi^j(\phi^j+\rho)} - \frac{1}{k(k+\rho)}\right] \\ & + \frac{\phi^j \bar{s}^j}{\rho}\left[-\frac{\alpha_0}{\alpha_1} + \frac{\alpha_1}{\alpha_0\alpha_2} - \frac{\alpha_1}{\phi^j(\phi^j+\rho)\alpha_0}\frac{1}{\rho^2} + \frac{\alpha_1}{\alpha_2\alpha_0(-(\rho+\alpha_2))} + \frac{1}{\rho^2}\right]\end{aligned} \tag{5.23}$$

$$\zeta_1^j = \frac{\alpha_1}{\alpha_0}\left(\frac{1}{\rho+\phi^j} - \frac{1}{\rho}\left(\frac{\alpha_1}{\alpha_0} - 1\right)\right) - \frac{1}{\alpha_2}\frac{\alpha_1}{\alpha_0} + \frac{2}{\rho} \tag{5.24}$$

$$\zeta_2^j = \frac{1}{\rho+\phi^j} - \frac{1}{\rho}\left(\frac{\alpha_1}{\alpha_0} - 1\right) \tag{5.25}$$

$$\zeta_3^j = \frac{a\phi^j \bar{s}^j \bar{Y} k}{\alpha_0}\left(\frac{1}{\rho+\phi^j} - \frac{1}{\rho+k}\right) \tag{5.26}$$

and

$$\alpha_0 = ak - k + a\phi^j + av\theta_{CF}^j \tag{5.27}$$

$$\alpha_1 = \phi^j - ak\bar{Y} + a\lambda v\theta_{CF}^j + a\phi^j \bar{s}^j \bar{Y} \tag{5.28}$$

$$\alpha_2 = a(k + \phi^j + v\theta_{CF}^j). \tag{5.29}$$

It follows from Proposition 6 that the price of the risky asset j depends on the current market conditions (Y_t) as well as the current share of consumption of the dividend process (s_t^j).

Proposition 7. *I apply Itô's lemma to the equilibrium price of the risky asset j from equation (5.67) and derive the equilibrium volatility of the risky asset j ($\sigma_R^j(Y_t)$).*

$$\sigma_R^j(Y_t, s_t^j) = \sigma_C(Y_t) - \left(\gamma_1^j(\theta_{CF}^j) - \frac{aY_t}{g_t}\right) v\sigma_C(Y_t) + \gamma_2^j(\theta_{CF}^j)\sigma^j(s_t)s_t^j, \tag{5.30}$$

where

$$\gamma_1^j(\theta_{CF}^j) = \frac{\zeta_1^j + \zeta_2^j Y_t}{\zeta_0^j + \zeta_1^j s_t^j + \zeta_2^j s_t^j Y_t + \zeta_3^j Y_t} \tag{5.31}$$

and

$$\gamma_2^j(\theta_{CF}^j) = \frac{\zeta_3^j + \zeta_2^j s_t^j}{\zeta_0^j + \zeta_1^j s_t^j + \zeta_2^j s_t^j Y_t + \zeta_3^j Y_t}. \tag{5.32}$$

The return volatility of the risky asset j is driven by three components: 1) shocks to the aggregate consumption, 2) shocks to the state variable Y_t and 3) shocks to the dynamics consumption share s_t^j. The sensitivity of return volatility to shocks to the state variable and the consumption share is described with constant parameters $\gamma_1^j(\theta_{CF}^j)$ and $\gamma_2^j(\theta_{CF}^j)$, respectively, and both depend on the heterogeneous cash-flow risk of asset j.

Proposition 8. *The equilibrium expected excess return of the risky asset j at time t, r_t^j, is given by*

$$\begin{aligned} r_t^j(Y_t, s_t^j) &= \mathrm{E}_t(dR_P^j - r_t dt) \\ &= \sigma_M(Y_t)\sigma_R^j(Y_t)dt \\ &= \sigma_C(Y_t)\left(1 + av\frac{Y_t}{g_t}\right)\left(\sigma_C(Y_t) - \left(\gamma_1^j(\theta_{CF}^j) - \frac{a}{g_t}\right) v\sigma_C(Y_t)Y_t \right. \\ &\qquad \left. + \gamma_2^j(\theta_{CF}^j)\sigma^j(s_t)s_t^j\right), \end{aligned} \tag{5.33}$$

where dR_P^j is the total return on the risky asset j at time t, $dR_P^j = (dP_t^j + D_t^j dt)P_t^j$.

Conditional Dependence of Expected Returns

The conditional measure of firm's risk (CAPM β^j) is associated with shocks to the cash-flow process and the discount-rate process driven by the state-variable Y_t. The effect of heterogeneous cash-flow risk (θ^j_{CF}) on the firm's risk thus depends on the current market conditions (Y_t) and the current value of the firm consumption share (s^j_t).

Proposition 9. *The conditional beta of asset j is time-varying and depends on the market conditions described by the state variable Y_t and the current value of the dividend share s^j_t.*

$$\begin{aligned}
\beta^j(Y_t, s^j_t) &= \frac{\text{cov}_t(r^j_t, r^m_t)}{\text{var}_t(r^m_t)} \\
&= \frac{\sigma^j_R(Y_t, s^j_t)\sigma_R(Y_t)'}{\sigma_R(Y_t)\sigma_R(Y_t)'} \\
&= \frac{\sigma_C(Y_t) - \left(\gamma^j_1(\theta^j_{CF}) - \frac{a}{g_t}\right) v\sigma_C(Y_t)Y_t + \gamma^j_2(\theta^j_{CF})\sigma^j(s_t)s^j_t}{\left(1 + \frac{aY_t}{g_t}\frac{kv}{(\rho a(Y_t - \bar{Y}) + \rho + k)}\right)\sigma_C(Y_t)}
\end{aligned} \tag{5.34}$$

The covariance between returns on asset j and the market is affected by heterogeneous cash-flow risk through parameters $\gamma^j_1(\theta^j_{CF})$ and $\gamma^j_2(\theta^j_{CF})$. The effect of the heterogeneous cash-flow risk on the conditional dependence is further studied in Section 5.3.

I explore whether the effect of heterogeneous cash-flow risk on conditional return dependence comes from the discount-rate or the cash-flow channel. I decompose the equilibrium conditional β ($\beta^j(Y_t, s^j_t)$) into its cash-flow (β^j_{CF}) and discount-rate component (β^j_{DISC}): $\beta^j = \beta^j_{CF} + \beta^j_{DISC}$, which allows me to study both of them separately.

Proposition 10. *The equilibrium cash-flow and discount-rate betas for asset j are* *given by*

$$\beta^j_{CF}(Y_t, s^j_t) = \frac{\frac{\partial P^j_t}{\partial s^j_t}\frac{s^j_t}{P^j_t}\sigma^j(s_t)}{1+\frac{\partial P_t}{\partial Y_t}\frac{Y_t}{P_t}} = \frac{\gamma^j_2(\theta^j_{CF})s^j_t\sigma^j(s_t)}{\sigma_C(Y_t)+akv\frac{\sigma_C(Y_t)Y_t}{g_t(\rho a(Y_t-\bar{Y})+\rho+k)}} \qquad (5.35)$$

and

$$\beta^j_{DISC}(Y_t, s^j_t) = \frac{1+\frac{\partial P^j_t}{\partial Y_t}\frac{Y_t}{P^j_t}\sigma_C(Y_t)}{1+\frac{\partial P_t}{\partial Y_t}\frac{Y_t}{P_t}} = \frac{\sigma_C(Y_t)-\left(\gamma^j_1(\theta^j_{CF})-\frac{a}{g_t}\right)v\sigma_C(Y_t)Y_t}{\sigma_C+akv\frac{\sigma_C(Y_t)Y_t}{g_t(\rho a(Y_t-\bar{Y})+\rho+k)}}. \qquad (5.36)$$

I calibrate the model in Section 5.3 and study the effects of the heterogeneous cash-flow risk (θ^j_{CF}) on the conditional dependence measures. I am particularly interested in assessing the asymmetries in the conditional dependence during market downturns relative to market upturns. The degree of asymmetric return dependence is captured by the slope of the conditional β as a function of the state variable Y_t. The higher the slope of β, the higher the degree of asymmetric dependence, because the difference between conditional dependence in bad states versus good states will increase.

Table 5.1: Panel A reports the calibration parameters. Panel B displays a set of moments for the aggregate stock market observed between 1952 and 2015: the risk premium (r_m), risk-free rate, consumption to price ratio (PC) and sharpe ratio (SR). It compares the observed values with the same moments in simulated data obtained from a 10,000-year simulation of the model. Two models are compared: Model (1) represents the unrestricted version of the model with preference shocks as described in from Section 5.2. Model (2) refers to the model without preference shocks, that is when $a = 0$.

Panel A	a	ρ	k	$\bar{Y}$	λ	$\bar{v}$	μ_C	σ_{max}	θ^j_{CF}
	0.0385	0.0416	0.1567	34	20	1.1194	0.0218	0.064	(-0.02; 0.02)

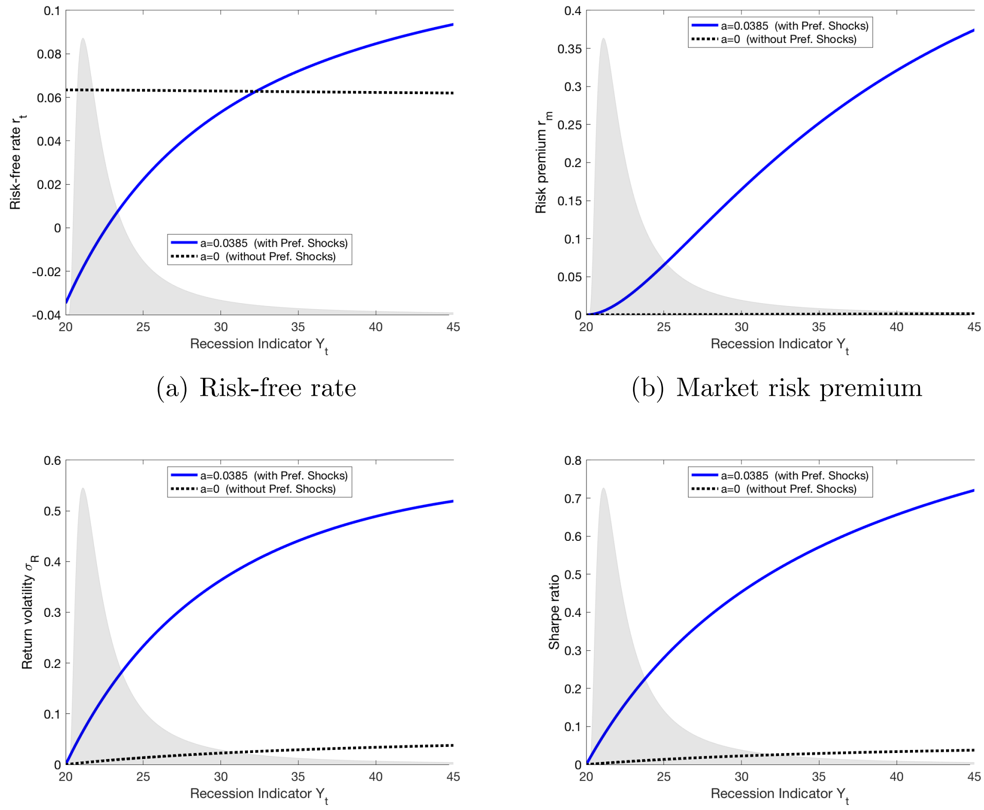
Panel B	r_m	r_m (Std)	r_f	r_f (Std)	PC	PC (Std)	SR
Data (1952-2015)	0.0786	0.1660	0.0186	0.0251	35.8878	16.5892	0.3612
Model (1): with pref. shocks	0.0734	0.1843	0.0110	0.0368	29.7596	5.5446	0.2354
Model (2): without pref. shocks	0.0003	0.0117	0.0631	0.0005	24.0385	0.0000	0.0117

5.3 Model Predictions

The Aggregate Economy

The model proposed in Section 5.2 is calibrated to fit the aggregate US data between 1952 and 2015. In particular, I choose calibration parameters to fit the main moments of asset prices including the risk-free rate, market risk premium, price-to-consumption ratio and sharpe ratio observed in the US between 1952 and 2015. The parameters describing the recession indicator dynamics are from Santos and Veronesi (2017). Using parameters from Panel A in Table 5.1, I simulate 10,000 years of quarterly data and report the aggregate moments in Panel B. I consider two distinct models: with preference shocks (Model (1)) and without preference shocks (Model (2)). Model (2) assumes that the parameter a is equal to zero, which shuts down the preference shocks effect.

Aggregate Market: The Effect of Preference Shocks



(a) Risk-free rate

(b) Market risk premium

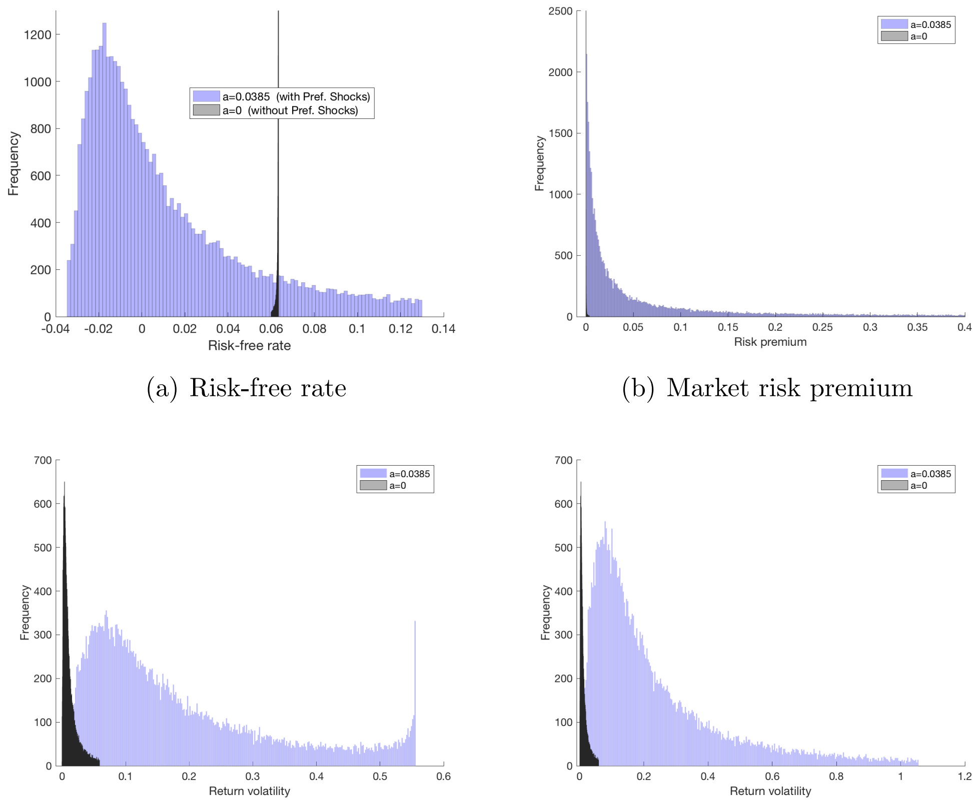
(c) Return volatility

(d) Sharpe ratio

Figure 5.1: This figure illustrates the effects of the preference shocks on the equilibrium risk-free rate (a), market-wide risk premium (b), return volatility (c), and the sharpe ratio of the market portfolio (d) as a function of the recession indicator Y_t. The shaded area represents the probability density of the state variable Y_t. Model (1) with preference shocks is represented by blue line and Model (2) is depicted using a black dotted line.

Model (1) fits well the US aggregate asset pricing moments while Model (2) cannot sufficiently explain the observed time variation of asset prices. In particular, Model (1) generates a significantly larger and realistic market risk premium, return volatility and Sharpe ratio relative to Model (2). In Model (2), the risk-free rate is too large and almost deterministic, the generated risk premium is close to zero and the Sharpe ratio is too low relative to the observed values. The only variation that we can observe in moments from Model (2) comes from the stochastic component of the consumption growth volatility. This variation is, however, too low to explain highly volatile asset prices. These findings suggest that the presence of preference shocks is important to generate a sufficient time variation of asset prices.

Aggregate Market: Simulations of the State Variable Y_t



(a) Risk-free rate (b) Market risk premium

(c) Return volatility (d) Sharpe ratio

Figure 5.2: This figure shows the effect of preference shocks (with $a = 0.0385$, blue area) on the distribution of the simulated equilibrium risk-free rate (a), market-wide risk premium (b), market volatility of returns (c), and the sharpe ratio of the market portfolio (d). The calibrated moments are compared to moments based on the model without preference shocks ($a = 0$, black area). The values are based on 10,000 years of simulated quarterly data of Y_t.

The conditional moments implied by Model (1) are substantially affected by the state variable Y_t, see the black line from Figure 5.1. In the proposed Model (1), all the reported moments that include the risk-free rate, market risk premium, return volatility of the market and the sharpe ratio are positively related with the recession indicator. In the model without the presence of preference shocks (black dotted line from Figure 5.1), the state variable has little effect on the reported moments of asset prices. Moreover, there is no other potential source of time variation in Model (2) and all the reported moments are thus too flat with a low standard deviation, see the histogram of simulated moments from Figure 5.2. This implies that preference shocks drive most of the variation of asset prices in Model (2).

The model predictions based on simulations suggest that the proposed model that considers preference shocks does surprisingly well in terms of fitting the observed data, considering the simplistic form of the model. The proposed model does not include external habits or long-run risks and is still able to yield and match important features of asset prices.

The model proposed in this paper deviates from most existing theories by assuming that investors experience preference shocks. In equilibrium, when the recession indicator is at its mean level, the value of the g_t function is one and the preference shock is zero. Any deviation of the recession indicator from its equilibrium long-term mean leads to a non-zero preference shock. For example, if the recession indicator is above its long-term mean (in bad times), investors experience a positive preference shock and become more sensitive to each unit change in their utility.

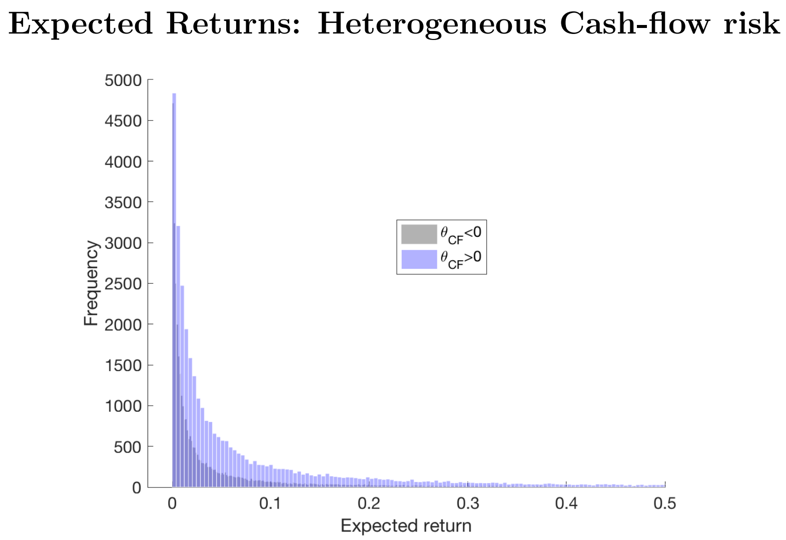


Figure 5.3: The distribution of the simulated expected returns for assets with negative cash-flow (CF) risk and positive CF risk: $\theta^j_{CF} = -0.02$ (grey area), and $\theta^j_{CF} = 0.02$ (blue area). Simulations of 10,000-year quarterly time series of prices.

Individual Risky Assets

I consider two risky assets that differ only in their level of cash-flow risk. In particular, I consider a risky asset with negative cash-flow risk: $\theta^j_{CF} = -0.02$ and a risky asset with positive cash-flow risk: $\theta^j_{CF} = 0.02$. I assume that all assets have homogeneous long-term mean of the consumption share ($\bar{s}^j = 0.05, \forall j$), homogeneous volatility of the consumption share ($\sigma^j(s_t) = 0.05, \forall j$), and homogeneous mean-reversion parameter of the consumption share ($\psi^j = 0.05$), see Panel A from Table 5.1. This setup allows me to focus solely on the effects of heterogeneous cash-flow risk on asset prices and the asymmetric return dependence. I use the simulated time series of the state variable Y_t that is based on 10,000 simulations of quarterly data to get expected returns of the risky assets and the conditional dependence measures.

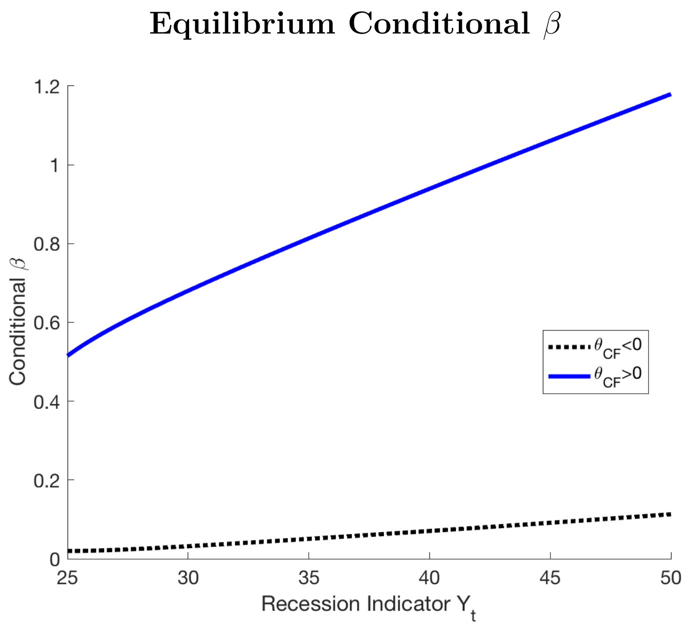


Figure 5.4: Conditional β described as a function of the recession indicator Y_t. This figure shows the equilibrium conditional β for two types of assets with negative cash-flow (CF) risk (black dotted line) and positive CF risk (blue line).

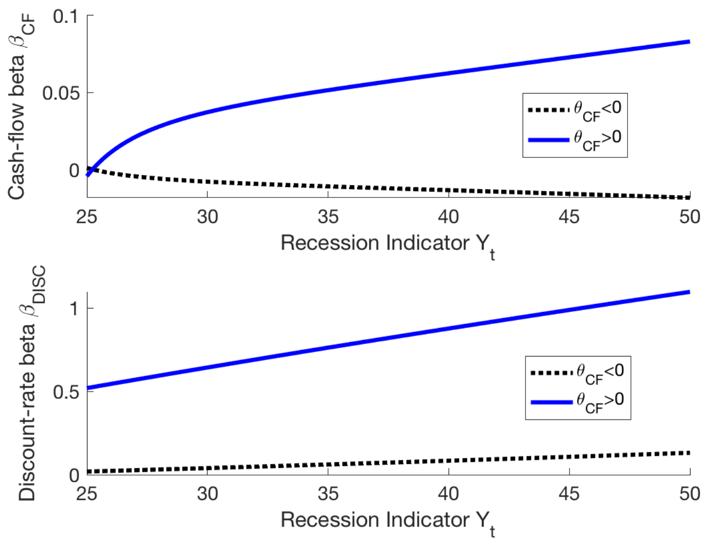
The first and the second moment of the equilibrium distribution of expected returns are positively affected by the asset-level heterogeneous cash-flow risk, see Figure 5.3. I find that the high cash-flow risk asset has a higher mean expected return and a higher volatility of expected returns. The effect of the heterogeneous cash-flow risk is even stronger on the second moment, i.e. the volatility of expected returns.

The main aim of this paper is to explore whether there is any link between fundamental cash-flow risks of firms and the degree of asymmetric dependence between stock and market returns. I first examine the effect of heterogeneous cash-flow risk on the time variation of conditional βs. I find that cash-flow risk positively affects the conditional level of dependence (conditional β), see Figure 5.4. The proposed model predicts that assets with a negative cash-flow risk, i.e. $\theta_{CF} < 0$, are expected to have relatively lower conditional CAPM βs, a significantly lower time variation of CAPM β and a lower degree of asymmetric dependence.

This can be seen from the value and the relatively flat slope of the equilibrium level of the model-implied conditional β for the asset with a negative cash-flow risk (black dotted line from Figure 5.4).

On the other hand, a high cash-flow risk asset with $\theta_{CF} > 0$ exhibits a significantly higher degree of asymmetric dependence, see the blue line from Figure 5.4. The dependence between stock returns of a high cash-flow risk asset and market returns is found to be particularly strong during market downturn periods when the recession indicator value Y_t is high.

Equilibrium Cash-flow (β_{CF}) and discount-rate β (β_{DISC})



(a)

Figure 5.5: Cash-flow and discount-rate β described as a function of the recession indicator Y_t. Panel (a) shows the equilibrium cash-flow β for two types of assets with negative cash-flow (CF) risk (black dotted line) and positive CF risk (blue line). Panel (b) depicts the conditional discount-rate β for two types of assets with negative cash-flow (CF) risk (black dotted line) and positive CF risk (blue line).

I show in Figure 5.5 that heterogeneous cash flow risk affects both the cash-flow and discount-rate β. This is because the firms' covariance between cash-flow growth and consumption growth affects both the price sensitivity to economic shocks (discount-rate channel) as well as the sensitivity of the asset price to shocks in the asset's cash-flows (cash-flow channel).

5.4 Data

Aggregate Consumption

The existing empirical evidence suggests that consumption asset-pricing models fail to explain asset prices (Breeden et al., 1989; Kroencke, 2017; Savov, 2011). There is a number of potential explanations why the available consumption data performs poorly to measure consumption risk. First, consumption asset-pricing models price assets with respect to changes in aggregate consumption between two points in time (Breeden et al., 1989). The reported consumption is, however, not consumed at the same time as reported and the aggregate consumption values are thus affected by a "summation bias" (Breeden et al., 1989).

Second, consumption data is time-aggregated. Available data on consumption provides total volumes of expenditures on goods and services over a period of time. The published values of NIPA expenditures are flow estimates of consumption collected during a certain period. Consumption models, on the other hand, require point-in-time values of consumption. This leads to the "time-aggregation bias".

Third, consumption measures based on National Income and Product Accounts (NIPA) are subject to "measurement error" due to infrequent reporting of consumption by the Bureau of Economic Analysis (BEA). NIPA consumption is estimated based on monthly retail trade survey data. An insufficient sample size may lead to sampling error. The annual data is based on a more comprehensive set of survey, which may lower the overall effect of the sampling bias.

Fourth, econometricians filter NIPA consumption to mitigate the measurement bias that arises due to the imperfections of available data. These imperfections may come from reporting errors or misclassification biases (Kroencke, 2017). If the BEA, who publishes NIPA values, acknowledges these measurement errors, they may decide to smooth the consumption time series, which may lower the stock market covariances (Daniel and Marshall, 1997).

To mitigate the effects of the biases inherent in NIPA consumption data, I use a number of proxies of consumption shocks, including the unfiltered NIPA consumption Kroencke (2017) and alternative measures (indirect) proxies of the business cycle.

Direct Measure of Consumption

NIPA consumption produced by BEA that is based on price indexes for personal consumption for nondurable goods and services.[1] The data is available on monthly, quarterly and annual frequency. I choose the quarterly frequency because it is based on a considerable larger retail trade survey compared to monthly data, which yields a lower sampling bias.

Unfiltered Consumption

The annual NIPA consumption is filtered by BEA to account for errors inherent in data described above. This filtering procedure may decrease the explanatory power of any NIPA consumption-based variable to explain the variation in asset prices. Kroencke (2017) applies an econometric procedure to reverse the filtering contained in NIPA consumption and correct for the time-aggregation bias inherent in consumption data. I collect the unfiltered consumption growth from Tim Kroencke's personal website.[2] Figure 5.6 demonstrates the effect of the Kroencke (2017)'s unfiltering procedure. The unfiltered consumption growth exhibits a sig-

[1] The consumption data was retrieved from the Federal Reserve Bank in St. Louis Economic Data: https://fred.stlouisfed.org/ in July 2018.

[2] Downloaded from https://sites.google.com/site/kroencketim/data-programs in January 2018.

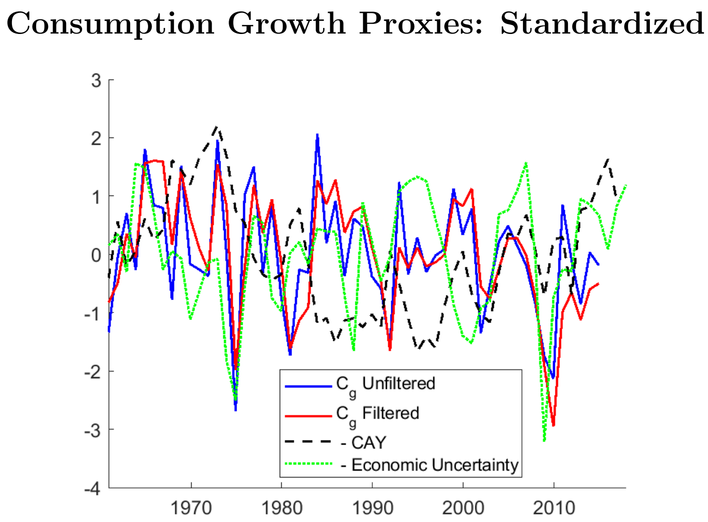


Figure 5.6: Consumption Growth Proxies (1960-2015): the filtered measure of NIPA consumption growth (red line), the unfiltered NIPA consumption data (blue line) (Kroencke, 2017) and alternative measures (indirect) based on the inverse of the Lettau and Ludvigson (2001)'s 'cay' variable (black dashed line) and the inverse of the Jurado et al. (2015)'s economic uncertainty index (green dotted line).

nificantly larger amount of time variation relative to the original time series of NIPA consumption growth. For further details about the unfiltering procedure, see Kroencke (2017).

Indirect Measures of Consumption Shocks

I note that in the proposed model, the aggregate consumption dynamics dC_t described in (5.1) and the dynamics of the recession indicator dY_t (5.3) are perfectly negatively correlated. As a result, I choose to proxy for shocks in consumption using shocks to the recession indicator (with the opposite direction) when estimating the industry-level cash-flow risk.

$$\text{cov}\left(\frac{ds_t}{s_t}, \frac{dC_t}{C_t}\right) = -\text{cov}\left(\frac{ds_t}{s_t}, \frac{dY_t}{Y_t}\right) \tag{5.37}$$

I use indirect measures of consumption shocks proxied using the Lettau and Ludvigson (2001)'s 'CAY' variable and the Jurado, Ludvigson, and Ng (2015)'s measure of economic uncertainty. These measures are based on a larger set of variables, have a substantially higher variation than NIPA consumption, and may, therefore, suit better to explain highly volatile asset prices.

The (Lettau and Ludvigson, 2001) 'CAY' variable is the trend deviation term of aggregate consumption regressed on asset holdings and aggregate wealth.[1] The 'economic uncertainty' variable represents the Jurado et al. (2015)'s economic uncertainty over one-month horizon.[2] The negative values of the 'CAY' and 'economic uncertainty' variables are reported in Figure 5.6 because both of these variables are considered to be countercyclical (Jurado et al., 2015; Lettau and Ludvigson, 2001).

Firm Cash Flows

The estimation of the complex dynamic structure of the cash-flow processes of risky assets defined in equation (5.16) requires firm-level cash-flow data with a sufficiently high frequency of observations. The US firm fundamental data is only available with annual or quarterly frequency. Dividends payments, the main source of income to shareholders, are also paid out infrequently. The low frequency of cash-flow data (typically quarterly) complicates the estimation of firm-level cash-flow risk.

I collect security data on US listed firms from the WRDS CRSP-Compustat Merged database from the beginning of the database in 1959 until 2017. I aggregate the firm-level data into 49 Fama-French industries to assure that all assets have a sufficiently long time series of data to estimate the cash-flow covariance risk. I limit my attention to firms listed on NYSE (share code 1). I collect monthly information about the firm identifier ('permno'), total stock return ('ret'), close price ('prc') and number of shares outstanding ('shrout') from the WRDS CRSP

[1] Retrieved from https://sites.google.com/view/martinlettau/data on July 1, 2018
[2] Downloaded from https://www.sydneyludvigson.com/data-and-appendixes/ on July 1, 2018

Table 5.2: Cash-Flow Items: Unconditional Values. Descriptive Statistics for cash-flow items used to estimate net payout: dividends (Div) and net equity repurchases (Equity Rep). The values are represented as a fraction of the total market value of assets. Net payout growth (NP Growth) is the annual growth of the net payout (NP) to market value of assets ratio. Fama French 49 Industries data is collected from 1960 until December 2015

FF49	Industry	NP	NP Growth	Div	Equity Rep
1	Agriculture	0.782	-0.149	0.662	0.120
2	Food Products	0.915	-0.020	1.283	-0.279
3	Candy & Soda	0.628	-0.364	1.498	-0.870
4	Beer & Liquor	0.050	0.033	1.074	-1.024
5	Tobacco Products	2.758	0.136	3.137	-0.378
6	Recreation	1.903	-0.173	0.840	1.073
7	Entertainment	1.872	-0.044	0.843	1.032
8	Printing and Publishing	0.794	0.035	1.459	-0.664
9	Consumer Goods	0.725	-0.006	1.277	-0.551
10	Apparel	0.747	-0.070	0.810	-0.063
11	Healthcare	1.571	-0.021	0.289	1.295
12	Medical Equipment	0.534	-0.060	0.517	0.020
13	Pharmaceutical Products	1.454	0.008	0.919	0.543
14	Chemicals	0.870	0.023	1.244	-0.368
15	Rubber and Plastic Products	0.854	-0.046	1.149	-0.294
16	Textiles	0.701	0.070	0.531	0.170
17	Construction Materials	1.040	-0.059	1.118	-0.076
18	Construction	0.855	-0.040	0.462	0.398
19	Steel Works Etc.	1.503	-0.092	1.022	0.487
20	Fabricated Products	1.338	0.075	0.950	0.389
21	Machinery	0.901	-0.026	0.963	-0.055
22	Electrical Equipment	1.140	-0.097	1.435	-0.293
23	Automobiles and Trucks	0.930	-0.016	1.072	-0.126
24	Aircraft	0.206	-0.052	0.711	-0.495
25	Shipbuilding, Railroad Equipment	1.012	0.131	1.449	-0.437
26	Defense	1.353	0.011	1.988	-0.635
27	Precious Metals	2.337	-0.049	0.545	1.796
28	Non-Metallic and Industrial Metal Mining	2.432	0.012	1.429	1.009
29	Coal	3.322	-0.086	1.947	1.415
30	Petroleum and Natural Gas	2.828	-0.003	0.864	1.974
31	Utilities	2.744	0.001	2.106	0.650
32	Communication	1.449	-0.011	1.117	0.347
33	Personal Services	0.360	-0.027	0.593	-0.231
34	Business Services	0.906	-0.094	0.622	0.293
35	Computers	0.620	-0.021	0.437	0.186
36	Computer Software	1.602	-0.082	0.456	1.149
37	Electronic Equipment	0.948	-0.057	0.547	0.402
38	Measuring and Control Equipment	0.371	-0.049	0.716	-0.352
39	Business Supplies	1.059	-0.011	1.685	-0.615
40	Shipping Containers	0.812	0.091	1.168	-0.351
41	Transportation	1.410	0.029	0.815	0.599
42	Wholesale	1.152	-0.043	0.817	0.345
43	Retail	0.484	-0.033	0.751	-0.265
44	Restaurants, Hotels, Motels	0.468	-0.047	0.607	-0.124
45	Banking	2.362	-0.002	1.156	1.222
46	Insurance	0.509	-0.048	0.555	-0.041
47	Real Estate	2.080	-0.060	0.803	1.285
48	Trading	2.264	0.025	1.958	0.329
49	Other	1.786	-0.013	0.410	1.407

Monthly Security File. I retrieve information on the monthly market return and the risk-free rate from the WRDS Fama-French Database.

Cash-flow data comes from from the WRDS Compustat Fundamental Annual File. I use the equity-holder definition of firm cash flows, and define the net payout (NP) as the sum of all dividends paid plus plus net equity repurchases.

$$NP = Div + Eq\_Rep \tag{5.38}$$

where Div are Cash Dividends and Eq_Rep are Purchases of Common and Preferred Stock, Table 5.2 provides a descriptive summary of the industry-level cash-flow items. I aggregate the firm-level NP and MVA into industry levels. I limit attention to firms that have at least five years of data and remove all observations where the value of common equity ('ceq') is negative to remove any distressed firms from my sample.

5.5 Empirical Tests

Estimation of Cash-flow Risk

I estimate the cash-flow risk (θ^j_{CF}) individually for all 49 Fama-French industries, where the cash-flow risk of industry j is the covariance between cash-flow and consumption growth (Menzly et al., 2004)

$$\theta^j_{CF} = \text{cov}_t\left(\frac{ds^j_t}{s^j_t}, \frac{dC_t}{C_t}\right), \tag{5.39}$$

and s^j_t is the share of output that the risky security j produces and C_t is the aggregate output at time t. I calculate the share of output for each industry using the information about the industry-level net payout to aggregate consumption ratio. At each year t, I use data from past 10 years to estimate the cash-flow risk level $\theta^j_{CF}(t)$) for industry j. I estimate $\theta^j_{CF}(t)$ on a yearly-rolling window basis and

Table 5.3: Cash-Flow Risk: Unconditional Values. CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Filt.)), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Unf.)), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)). Fama French 49 Industries data is collected from 1960 until December 2015.

FF49 Id	Industry	θ^j_{CF} (Filt.)	θ^j_{CF} (Unf.)	θ^j_{CF} (CAY)	θ^j_{CF} (Unc.)
1	Agriculture	0.160	0.306	0.230	0.407
2	Food Products	-0.146	-0.135	0.084	0.112
3	Candy & Soda	0.222	0.055	-0.200	-0.169
4	Beer & Liquor	0.069	-0.043	-0.015	-0.515
5	Tobacco Products	-0.298	-0.413	0.128	0.011
6	Recreation	0.020	-0.073	0.259	-0.051
7	Entertainment	0.249	0.279	-0.165	-0.040
8	Printing and Publishing	0.001	-0.037	0.118	-0.403
9	Consumer Goods	-0.140	-0.184	-0.023	0.014
10	Apparel	-0.164	-0.180	-0.093	-0.059
11	Healthcare	0.163	0.162	0.007	0.084
12	Medical Equipment	-0.052	-0.206	-0.147	-0.046
13	Pharmaceutical Products	-0.063	-0.092	-0.022	0.131
14	Chemicals	-0.074	-0.008	0.031	0.227
15	Rubber and Plastic Products	-0.107	-0.140	-0.110	-0.309
16	Textiles	0.128	0.115	0.062	-0.052
17	Construction Materials	0.059	0.001	-0.227	0.068
18	Construction	-0.013	0.069	0.031	0.053
19	Steel Works Etc.	-0.073	-0.072	0.009	0.096
20	Fabricated Products	-0.055	-0.052	-0.008	0.062
21	Machinery	-0.003	-0.029	0.107	0.140
22	Electrical Equipment	-0.075	-0.162	-0.107	-0.191
23	Automobiles and Trucks	0.010	-0.092	-0.110	0.028
24	Aircraft	0.195	0.116	-0.010	0.464
25	Shipbuilding, Railroad Equip.	-0.013	0.103	-0.036	-0.351
26	Defense	-0.188	-0.493	-0.084	0.307
27	Precious Metals	-0.219	-0.179	-0.087	-0.079
28	Non-Metal. and Ind. Metal Min.	-0.001	-0.023	0.054	0.118
29	Coal	-0.248	-0.063	-0.200	0.248
30	Petroleum and Natural Gas	0.011	0.062	-0.031	0.082
31	Utilities	-0.001	-0.034	-0.022	-0.001
32	Communication	-0.256	-0.318	-0.317	-0.364
33	Personal Services	-0.033	-0.046	-0.134	-0.074
34	Business Services	-0.003	0.058	-0.057	0.096
35	Computers	-0.038	-0.175	-0.116	0.023
36	Computer Software	-0.030	0.065	0.090	-0.009
37	Electronic Equipment	0.066	0.017	-0.013	-0.038
38	Measuring and Control Equip.	0.014	-0.028	-0.015	0.002
39	Business Supplies	-0.117	-0.095	-0.109	0.075
40	Shipping Containers	-0.288	-0.269	0.198	0.186
41	Transportation	-0.228	-0.204	0.176	-0.261
42	Wholesale	0.106	0.078	0.083	-0.308
43	Retail	-0.043	-0.034	0.057	0.259
44	Restaurants, Hotels, Motels	0.163	0.228	0.006	0.111
45	Banking	-0.105	-0.157	-0.147	-0.100
46	Insurance	0.106	0.026	-0.149	-0.039
47	Real Estate	-0.170	-0.328	0.022	0.154
48	Trading	0.069	0.085	-0.042	0.311
49	Other	-0.136	-0.020	0.090	-0.141

obtain a time-series of cash-flow risk levels for each industry. I also estimate the unconditional level of cash-flow risk for each industry and report results in Table 5.3.

There are substantial differences in the unconditional industry levels of cash-flow risk. I estimate four versions of the industry-level cash flow risk. Each year t, I estimate cash-flow risk for industry j using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)).

I find that a relatively high proportion of industries have negative cash-flow risk, that is a negative covariance between the aggregate consumption growth and firm cash-flow growth. I focus on the firm heterogeneity in cash-flow risk to examine whether cash-flow risk can account for the time variation in asymmetric return dependence. The sign and the magnitude of cash-flow risk has important implications for cash-flow dynamics and asset prices.

Consider a negative consumption shock. The sign of the asset-level cash-flow risk, that is the covariance between consumption growth and cash-flow growth, will determine whether an asset is a good or a bad hedge against bad economic conditions. If the covariance is negative, $\theta^j_{CF} < 0$, then given a negative shock to consumption, $\frac{dC_t}{C_t} < 0$, the asset j will constitute of a larger fraction of consumption because $\frac{ds^j_t}{s^j_t}$ will increase. This asset will thus serve as a hedge against bad times as it will likely pay out higher cash-flows to shareholders when consumption decreases.

Cross-sectional Tests

I test the model predictions from Section 5.3 and examine whether there is any link between the fundamental cash-flow risk of firms and the degree of asymmetric dependence of asset returns.

Conditional Dependence

I measure the conditional dependence of the 49 Fama-French industries using data divided into quintiles sorted in terms of the size of the market risk premium. Quintile 1 (Q1) refers to market upturn periods associated the largest market risk premium and quintile 5 (Q5) then indicates the lowest market risk premium levels, see Table 5.4. This approach helps to assess the state dependence of the conditional moments. I also sort industries in terms of their cash-flow risk levels to examine whether heterogeneous cash-flow risk affects conditional dependence of asset returns. I report the conditional dependence levels for industries with the highest unconditional level of cash-flow risk (Q1) and the lowest unconditional level of cash-flow risk (Q5).

Table 5.4: Conditional Dependence: This table reports the conditional values of the covariance and correlation between stock returns and market returns, the conditional CAPM β and the conditional return variance for industries with the highest unconditional cash-flow risk levels (from the highest quintile) and the lowest unconditional cash-flow risk levels (from the lowest quintile). The unfiltered consumption growth (Kroencke, 2017) is used to calculated cash-flow risk. All available US data between 1960 and 2015 is used.

	Good State (Q1)	Bad State (Q5)	Diff (Q5 - Q1)
Panel A		Conditional Covariance	
High CF risk (Q1)	0.00035	0.0024	0.0021
Low CF risk (Q5)	0.00028	0.0006	0.0003
		Conditional Return Correlation	
High CF risk (Q1)	0.3639	0.6996	0.3357
Low CF risk (Q5)	0.2981	0.2450	-0.0531
		Conditional CAPM beta	
High CF risk (Q1)	0.9003	1.6669	0.7666
Low CF risk (Q5)	0.7256	0.4237	-0.3019
		Conditional Return Variance	
High CF risk (Q1)	0.0029	0.0053	0.0023
Low CF risk (Q5)	0.0025	0.0025	0.0000
Market	0.0004	0.0015	0.0011

I find that the conditional covariance between stock and market returns is significantly higher during bad market states, see Panel A from Table 5.4. The difference between the conditional covariance in bad states versus good states is three times larger in industries with high cash-flow risk as compared with industries with low cash-flow risk. This finding confirms the model prediction that although the return dependence of all risky assets is positively linked with the recession indicator, high cash-flow risk assets are affected by market conditions relatively more. As a result, high cash-flow risk stocks are found to exhibit a relatively higher degree of risk that is related to the higher conditional dependence on market conditions.

The conditional correlation between high cash-flow risk industry returns and market returns is higher during market downturns than during market upturns, see Panel B from Table 5.4. The observed return correlation is 0.6696 in bad states versus 0.3639 in good states, which implies that assets with high fundamental cash-flow risk become significantly more correlated with market performance during bad times. Low cash-flow risk industries exhibit relatively symmetric correlations of returns: 0.2981 in bad states compared with 0.2450 in good states.

I find that the relation between the conditional variance of market returns and the market state is not monotonic. In fact, in both good market states associated with the highest market risk premium (Q1) and bad market states related with the lowest market risk premium (Q5), the market return variance is relatively high, see Panel C from Table 5.4. This relation also affects conditional βs. Note that in normal market states (Q3), the variance of market returns is extremely low and the conditional βs are consequently high for both assets with high and low cash-flow risk. The conditional βs are reported in Panel D from Table 5.4.

My findings confirm that there is a positive link between heterogeneous cash-flow risk of firms and asymmetric dependence of returns, see Figure 5.7. The

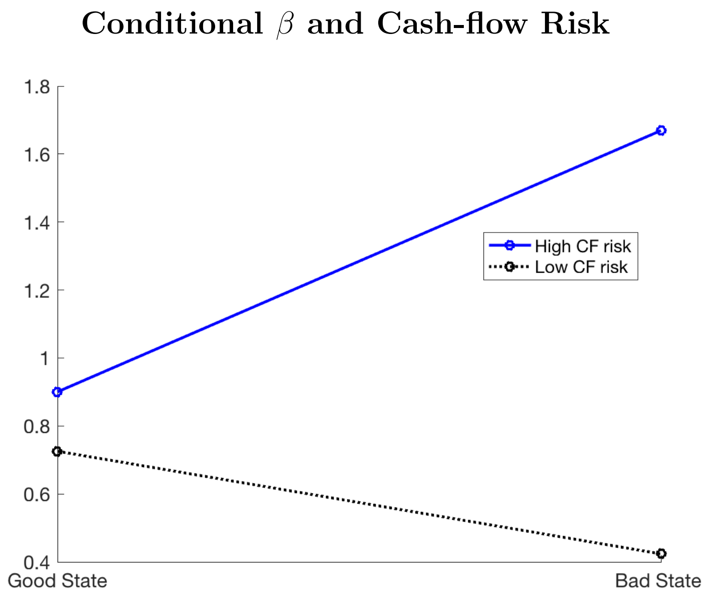


Figure 5.7: Conditional β in Good State (Q1) and Bad State (Q5) for industries with a high and low cash-flow risk from Table 5.4.

last column from Table 5.4 shows that the asymmetric dependence (Q5-Q1) is substantially higher for the high cash-flow risk industries relative to low cash-flow risk industries. The proposed model, however, does not predict high return volatility during periods of high market risk premia. Hence, it requires further research to extend the model to explain the non-monotonic shape of the observed relation between market volatility and market state.

Asymmetric Dependence between Stock and Market Returns

I formally measure the industry-level of asymmetric dependence using the Alcock and Hatherley (2016) Adjusted-J statistic (J^{Adj}). This statistic can distinguish between the various degrees of asymmetric dependence. Unlike the downside and upside β, the J^{Adj} combines information from a set of exceedance regions to measure conditional return dependence. The Adjusted J-statistic (J^{Adj}) adapts the J statistic proposed by Hong et al. (2007) so that it is β and idiosyncratic risk invariant, thereby improving its utility in empirical asset-pricing studies. The J^{Adj}

is defined by Alcock and Hatherley (2016) as

$$AD = J^{Adj} = \left[\operatorname{sgn}\left(\left[\tilde{\rho}^{+} - \tilde{\rho}^{-}\right]\mathbf{1}\right) T \left(\tilde{\rho}^{+} - \tilde{\rho}^{-}\right)' \hat{\Omega}^{-1}(\tilde{\rho}^{+} - \tilde{\rho}^{-})\right], \tag{5.40}$$

where $\tilde{\rho}^{+} = \{\tilde{\rho}^{+}(\delta_1), \tilde{\rho}^{+}(\delta_2), ..., \tilde{\rho}^{+}(\delta_N)\}$ and $\tilde{\rho}^{-} = \{\tilde{\rho}^{-}(\delta_1), \tilde{\rho}^{-}(\delta_2), ..., \tilde{\rho}^{-}(\delta_N)\}$, $\mathbf{1}$ is $N \times 1$ vector of ones, $\hat{\Omega}$ is an estimate of the variance-covariance matrix, (Hong et al., 2007). The conditional correlations are defined as follows, for $\delta_j \in \{\delta_1, ..., \delta_N\}$,

$$\tilde{\rho}^{+}(\delta_j) = \operatorname{corr}\left(\tilde{R}_{mt}, \tilde{R}_{it} | \tilde{R}_{mt} > \delta_j, \tilde{R}_{it} > \delta_j\right) \tag{5.41}$$

$$\tilde{\rho}^{-}(\delta_j) = \operatorname{corr}\left(\tilde{R}_{mt}, \tilde{R}_{it} | \tilde{R}_{mt} < -\delta_j, \tilde{R}_{it} < -\delta_j\right). \tag{5.42}$$

With symmetric dependence the value of J^{Adj} will be close to zero. A significant and non-zero value of J^{Adj} provides evidence of an asymmetry between the lower and upper-tail dependence.[1] Moreover, I multiply the original J^{Adj} by (-1) to satisfy that a positive (negative) value of the J^{Adj} refers to lower-tail (upper-tail) asymmetric dependence, which is a situation when stock returns are more correlated with market returns during market downturns (upturns) relative to market upturns (downturns).

The mean industry level of asymmetric dependence positive, see Table 5.5. This finding is consistent with existing empirical literature suggesting that the dependence of listed equity returns is higher during downturn periods relative to upturn periods, see, for example, Alcock and Hatherley (2016); Ang et al. (2006b);

[1] I replicate the procedure proposed by Alcock and Hatherley (2016) to estimate the Adjusted J-statistic (J^{Adj}) for each industry individually. First, for each set $\{R_{it}, R_{mt}\}_{t=1}^{T}$, I get $\hat{R}_{it} = R_{it} - \beta R_{mt}$, where R_{it} and R_{mt} is the excess return on asset i and market, and $\beta = \operatorname{cov}(R_{it}, R_{mt})/\sigma^2_{R_{mt}}$. The first transformation implies that each data set has a zero CAPM β, $\beta_{\hat{R}_{it}, R_{mt}} = 0$. Second, I standardize the data to get identical standard deviation of the CAPM regression residuals and get R^S_{mt} and $\hat{R}^S_{it}$. Third and the final transformation step sets the $\hat{\beta}$ to 1 by letting $\tilde{R}_{mt} = R^S_{mt}$ and $\tilde{R}_{it} = \hat{R}^S_{it} + R^S_{mt}$. After this transformation, all data sets have the same β and standard deviation of model residuals.

Chabi-Yo et al. (2017); Kelly and Jiang (2014); Weigert (2015).

Table 5.5: Descriptive Statistics for the variables used in the rolling-window regressions: CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)), industry-level asymmetric dependence (AD^j) estimated using the Alcock and Hatherley (2016)'s J^{Adj} statistic, the industry-level annual excess return (r^j), book-to-market ratio and log(size). Data from 1960 - 2015 are considered.

Variable	Mean	Std	Q1	Median	Q3	Skewness	Kurtosis
θ^j_{CF} (Dir. Filt.)	-0.026	0.234	-0.077	-0.009	0.036	0.073	7.032
θ^j_{CF} (Dir. Unfilt.)	-0.014	0.198	-0.052	-0.001	0.038	0.149	7.912
θ^j_{CF} (CAY)	-0.029	0.169	-0.088	-0.023	0.043	-0.833	4.742
θ^j_{CF} (Unc.)	-0.017	0.263	-0.096	-0.001	0.081	-0.017	6.623
AD^j	4.631	4.773	2.364	4.331	6.795	0.100	3.786
r^j	11.63%	16.35%	2.13%	9.67%	18.38%	1.429	5.033
BM	0.626	0.387	0.414	0.549	0.724	4.346	32.847
Log(size)	14.247	0.957	13.636	14.262	14.848	0.301	1.309

Cross-sectional Regressions

Industries with high levels of unconditional cash-flow risk tend to exhibit higher degrees of asymmetric dependence, see Figure 5.8. I test this relation using rolling-window regressions. The descriptive statistics of variables used in the regressions are reported in Table 5.5.

Each year t, I regress the industry-level of asymmetric dependence (AD^j), estimated using the Alcock and Hatherley (2016)'s J^{Adj} statistic based on monthly data from past 10 years, against industry-level cash-flow risk (θ^j_{CF}) estimated using data available from past 10 years and industry-level excess return (r^j) estimated using monthly data from past 10 years. The following measures of CF risk are considered: CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)) in Model (1), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)) in Model (2), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)) in Model (3), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)) in Model (4). I report the mean coefficients and t-statistics in Panel A from Table 5.6.

I find that the industry-degree of asymmetric dependence (AD^j) is positively related with the industry level of cash-flow risk (except for CF risk estimated using the Lettau and Ludvigson (2001)'s CAY variable). The regression results confirm the model predictions suggesting that high cash-flow risk assets exhibit higher degrees of asymmetric dependence.

Asymmetric Dependence (AD) and Cash-flow Risk

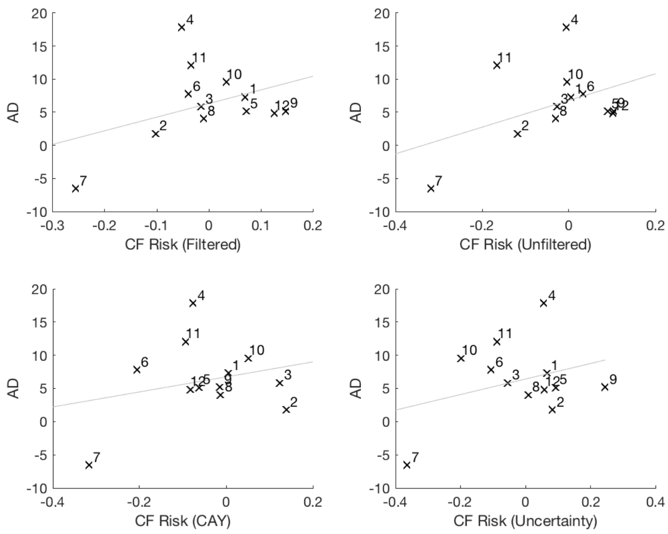


Figure 5.8: The relation between industry-level AD measured using the Alcock and Hatherley (2016)'s J^{Adj} and industry level of CF risk. CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)). Fama French 12 Industries data is collected from 1960 until December 2015. The industry id number is reported next to each scatter point.

Furthermore, I find empirical evidence confirming that fundamental cash-flow risk positively affects levels of conditional CAPM βs, see Panel B from Table 5.6. This finding is consistent with the model prediction from Figure 5.4. My findings suggest that the US industry levels of cash-flow risk affect both the degree of asymmetric dependence as well as the conditional level of dependence of equity returns.

Table 5.6: Rolling-window Regressions. Each year t, the industry-level of asymmetric dependence (AD^j) estimated using the Alcock and Hatherley (2016)'s J^{Adj} statistic, the industry-level excess return (r^j) and CAPM β estimated using past ten years of monthly data are regressed against industry-level CF risk (θ^j_{CF}) estimated using data available from past ten years. The following measures of CF risk are considered: CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)) in Model (1), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)) in Model (2), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)) in Model (3), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)) in Model (4). 49 Fama French industries are considered (1960-2015). This table presents mean regression coefficients and mean t-statistics in parenthesis. The Newey-West adjustment for standard errors is used.

Panel A	AD^j			
	Model (1)	Model (2)	Model (3)	Model (4)
θ^j_{CF} (Dir. Filt.)	1.214			
	[2.370]			
θ^j_{CF} (Dir. unfilt.)		1.758		
		[2.090]		
θ^j_{CF} (CAY)			0.547	
			[0.700]	
θ^j_{CF} (Unc.)				0.684
				[2.080]
Intercept	4.704	4.701	4.679	4.622
	[8.270]	[8.250]	[8.100]	[8.240]

Panel B	CAPM β^j			
	Model (1)	Model (2)	Model (3)	Model (4)
θ^j_{CF} (Dir. Filt.)	0.223			
	[2.770]			
θ^j_{CF} (Dir. Unfilt.)		0.178		
		[2.570]		
θ^j_{CF} (CAY)			0.166	
			[1.630]	
θ^j_{CF} (Unc.)				0.067
				[0.720]
Intercept	0.910	0.911	0.901	0.903
	[16.820]	[16.560]	[16.160]	[16.420]

Panel C	Excess return (r^j)			
	Model (1)	Model (2)	Model (3)	Model (4)
θ^j_{CF} (Dir. Filt.)	-0.007			
	[0.280]			
θ^j_{CF} (Dir. Unfilt.)		0.025		
		[0.970]		
θ^j_{CF} (CAY)			0.056	
			[1.950]	
θ^j_{CF} (Unc.)				0.022
				[2.730]
Intercept	0.167	0.169	0.169	0.171
	[9.250]	[10.540]	[8.830]	[9.010]
β^j	-0.060	-0.059	-0.060	-0.062
	[4.330]	[4.650]	[4.140]	[4.450]

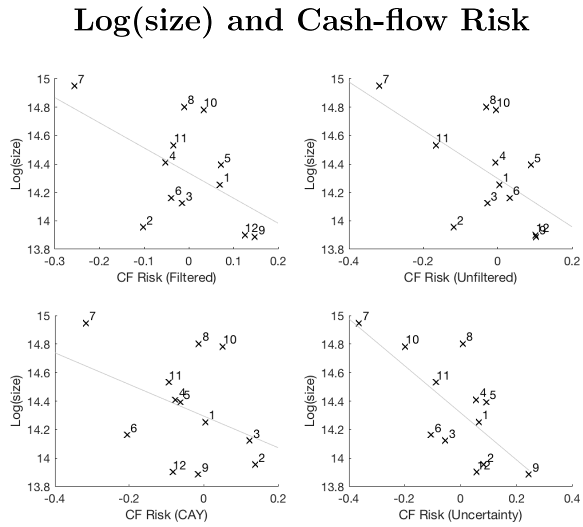


Figure 5.9: The relation between the industry log(size) and the industry level of CF risk. CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)). Fama-French 12 industry data is collected from 1960 until December 2015. The industry id number is reported next to each scatter point.

I explore whether industries with high fundamental cash-flow risk have higher excess returns in Panel C from Table 5.6. I regress the industry excess return (r^j) against the industry-level cash-flow risk (θ^j_{CF}) estimated using data from past ten years. I find a significant evidence of a positive relation between industry-level cash-flow risk and future excess returns (when the Lettau and Ludvigson (2001)'s CAY or Jurado et al. (2015)'s economic uncertainty variable are used). These results indicate that the cash-flow risk of industries represent a fundamental risk that explains the cross section of excess returns.

Size Premium

I present evidence that industries with high levels of unconditional cash-flow risk have generally low lower market value of equity, see Figure 5.9. This finding indicates that fundamental cash-flow risk of firms may be useful in explaining the value premia. I further test this relation conditionally using rolling-window regressions and report results in Table 5.7. I find that there is a significant negative relation between size of firms and cash-flow risk (except when cash-flow risk is measured using the Jurado et al. (2015)'s uncertainty variable), see Table 5.7.

My findings suggest that large firms have lower cash-flow risk values and can thus serve as better natural hedges against negative consumption shocks. This may explain why larger firms are perceived as less risky by market participants and exhibit lower excess returns.

Table 5.7: Rolling-window Regressions. Each year t, the industry-level book-to-market ratio and the log value of size estimated using the monthly data from past 10 years is regressed against industry-level CF risk (θ^j_{CF}) estimated using data available from past 10 years. The following measures of CF risk are considered: CF risk estimated using the filtered NIPA consumption data (θ^j_{CF} (Dir. Filt.)) in Model (1), the Kroencke (2017)'s unfiltered NIPA consumption data (θ^j_{CF} (Dir. Unfilt.)) in Model (2), the Lettau and Ludvigson (2001)'s CAY variable (θ^j_{CF} (CAY)) in Model (3), and the Jurado et al. (2015)'s economic uncertainty variable (θ^j_{CF} (Unc.)) in Model (4). 49 Fama-French industries are considered (1960-2015). This table presents mean regression coefficients and mean t-statistics in parenthesis. The Newey-West adjustment for standard errors is used.

	Log(size)			
	Model (1)	Model (2)	Model (3)	Model (4)
θ^j_{CF} (Dir. Filt.)	-0.345			
	[2.010]			
θ^j_{CF} (Dir. Unfilt.)		-0.294		
		[1.870]		
θ^j_{CF} (CAY)			-0.263	
			[2.440]	
θ^j_{CF} (Unc.)				0.025
				[0.180]
Intercept	14.225	14.222	14.245	14.234
	[85.270]	[82.760]	[87.570]	[88.750]

5.6 Conclusion

I examine the effect of fundamental cash-flow risk of firms on the asymmetric dependence between stock and market returns. Particularly, I explore why diversification benefits of certain assets disappear during market downturns. I find that portfolios with high fundamemtal cash-flow risk are likely to perform the worst during bad economic conditions because they exhibit a relatively high degree of asymmetric dependence.

I develop a consumption-based general equilibrium model with investors experiencing preference shocks that are exposed to heterogeneous cash-flow risks of assets. The model predicts that during periods associated with negative consumption shocks, assets with a low cash-flow risk will perform relatively better. In contrast, high cash-flow risk stocks are shown to exhibit a higher degree of asymmetric dependence.

The existence of preference shocks is important in explaining the conditional return dependence of assets. The effect of the preference shock makes investors value even more each additional unit of consumption, because their marginal utility depends positively on preference shocks. Furthermore, the presence of preference shocks can explain a rich spectrum of return risk premia. I find that the interaction between heterogeneous cash-flow risks of firms and preference shocks is crucial to explain the cross section of asset prices and the degree of asymmetric dependence.

These findings provide helpful insights on the sources of time variation in the cross section of conditional return dependence. This paper contributes to the existing literature by showing that high cash-flow risk stocks experience relatively higher return dependence on market conditions during bad times as compared to good times. I show that the fundamental cash-flow risk of firms affects both the cash-flow β as well as the discount-rate β of risky assets.

The model predictions are confirmed by US data. The paper uses a variety of measures of consumption that account for time-aggregation, measurement and sample bias inherent in the publicly available consumption data. The empirical evidence from US industries shows that the industry-level of asymmetric dependence is positively related with the industry level of cash-flow risk. The fundamental cash-flow risk also positively affects industry excess returns and CAPM β, which suggests that heterogeneous cash-flow risk is an important risk driver. Moreover, my results may help us understand why large firms exhibit lower excess returns. I show that firms with large market capitalization tend to have negative cash-flow risk and can thus serve as natural hedges against negative shocks to the aggregate economy.

5.7 Appendix

Proofs

Proof of Proposition 1

Proof. The first order condition of the social planner's problem described in equation (5.7) yields the Lagrange multiplier of the resource constraint, where $C_t^i = \psi^i C_t$.

$$u_C(C_t, Y_t) = e^{-\rho t} C_t^{-1} g_t(Y_t) = e^{-\rho t} C_t^{-1}(a(Y_t - \bar{Y}) + 1) = M_t. \tag{5.43}$$

□

Proof of Proposition 2

Proof. The conditional expected value and variance of the geometric Ornstein-Uhlenbeck process of Y_τ are $\mathrm{E}_t(Y_\tau|Y_t) = \bar{Y} + (Y_t - \bar{Y})e^{-k(\tau-t)}$ and $\mathrm{var}_t(Y_\tau|Y_t) = \frac{\sigma_C^2(Y_t)Y_t^2}{2k}(1 - e^{-2k(\tau-t)})$, respectively. The investor marginal utility is given by

$$M_t = e^{-\rho t} C_t^{-1}(a(Y_t - \bar{Y}) + 1) \tag{5.44}$$

and the price of the claim on aggregate consumption is

$$\begin{aligned} P_t &= \mathrm{E}_t\left[\int_t^\infty \frac{M_\tau}{M_t} C_\tau d\tau\right] \\ &= C_t g_t^{-1} \mathrm{E}_t\left[\int_t^\infty e^{-\rho(\tau-t)} g_\tau d\tau\right] \\ &= C_t g_t^{-1} \int_t^\infty e^{-\rho(\tau-t)} \left[a\left(\bar{Y} + (Y_t - \bar{Y})e^{-k(\tau-t)}\right) + 1 - a\bar{Y}\right] d\tau \\ &= C_t g_t^{-1}\left[\frac{a(Y_t - \bar{Y})}{\rho + k} + \frac{1}{\rho}\right]. \end{aligned} \tag{5.45}$$

□

Proof of Proposition 3

Proof. The dynamics of the stochastic discount process are described as

$$\frac{dM_t}{M_t} = -r_t dt - \sigma_{M,t} dZ_t^1, \tag{5.46}$$

where M_t is the investor marginal utility from Proposition 1:

$$M_t = e^{-\rho t} C_t^{-1} g_t. \tag{5.47}$$

Applying Itô's lemma to M_t leads to

$$\begin{aligned}\frac{dM_t}{M_t} = &-\left[\rho + \mu_C + +ak\frac{Y_t}{g_t}(1 - \bar{Y}/Y_t) + \left(1 + av\frac{Y_t}{g_t}\right)\sigma_C^2(Y_t)\right]dt \\ &-\left[\left(1 + av\frac{Y_t}{g_t}\right)\sigma_C(Y_t)\right]dZ_t^1\end{aligned} \tag{5.48}$$

To satisfy the local martingale property of the stochastic discount factor (M_t), the risk-free rate must be the negative value of drift term from the dM_t/M_t dynamics

$$r_t = \rho + \mu_C + +ak\frac{Y_t}{g_t}(1 - \bar{Y}/Y_t) + \left(1 + av\frac{Y_t}{g_t}\right)\sigma_C^2(Y_t) \tag{5.49}$$

and the market price of risk (σ_M) is the negative value of the diffusion term

$$\sigma_M = \left(1 + av\frac{Y_t}{g_t}\right)\sigma_C(Y_t). \tag{5.50}$$

□

Proof of Proposition 4

Proof. I apply Itô's lemma to the aggregate market price from equation 5.10 to derive the price dynamics of the aggregate portfolio. The equilibrium volatility ($\sigma_P(Y_t)$) is the diffusion term of the price dynamics process. The equilibrium price of the market portfolio is a function of the aggregate consumption C_t and the state variable Y_t (with scalars a, $\bar{Y}$, ρ and k).

$$P_t = \frac{C_t}{a(Y_t - \bar{Y}) + 1}\left[\frac{a(Y_t - \bar{Y})}{\rho + k} + \frac{1}{\rho}\right] = f(C_t, Y_t) \tag{5.51}$$

The dynamics are

$$\begin{aligned}dP_t = &P_t\left(\mu_C dt + \sigma_C(Y_t)dZ_t\right) + \frac{C_t}{\rho + k}\frac{ak}{\rho g_t^2}\left(k(\bar{Y} - Y_t)dt - v\sigma_C(Y_t)Y_t dZ_t\right) \\ &- \frac{C_t}{\rho + k}\frac{a^2 k}{\rho g_t^3}v^2\sigma_C^2(Y_t)Y_t^2 dt - \frac{1}{\rho + k}\frac{ak}{\rho g_t^2}vY_t\sigma_C^2(Y_t)dt,\end{aligned} \tag{5.52}$$

The equilibrium volatility of returns on the market portfolio is the diffusion term from the dP_t/P_t dynamics.

$$\sigma_R(C_t, Y_t) = \sigma_C(Y_t)\left(1 + \frac{akv}{g_t(a\rho(Y_t - \bar{Y}) + \rho + k)}Y_t\right) \tag{5.53}$$

□

Proof of Proposition 5 and 8

Proof. The local martingale property of the stochastic discount factor (M_t) imply that the drift of the $\frac{dM_t}{M_t}$ must cancel the drift term of the risk-less asset, rdt. Consider a risky asset with price X_t: $X_t = M_t Y_t$ and dynamics

$$\frac{dX_t}{X_t} = \frac{dM_t}{M_t} + \frac{dY_t}{Y_t} + \frac{dM_t}{M_t}\frac{dY_t}{Y_t}. \tag{5.54}$$

For X_t to be a local martingale, it must satisfy the following condition.

$$(\mu_t - r_t)dt = \sigma_{M,t}\sigma_{Y,t}dt, \tag{5.55}$$

where μ_t is the drift term of the Y_t dynamics.

□

Proof of Proposition 6

Proof. The price of the risky asset j is given by

$$P_t^j = C_t g_t^{-1} \int_t^{\infty} e^{-\rho(\tau - t)} \operatorname{E}_t\left(q_\tau^j\right) d\tau. \tag{5.56}$$

In order to find a closed-form solution to the price of the risky asset j from equation (5.20), I need to solve the integral $\int_t^\infty e^{-\rho(\tau-t)} \operatorname{E}_t\left(q_\tau^j\right)$. I follow the method used by Menzly et al. (2004) to find the solution to the stochastic SDE that drives q_t^j. I denote $X_t = (Y_t, q_t^j, s_t^j)'$. The dynamics of this vector are given by $dX_t = A_0 = A_1 X_t dt + \Sigma(Y_t, s_t^j)dZ_t^N$, where

$$A_0 = (k\bar{Y}, 0, \psi^j \bar{s}^j)' \text{ and } A_1 = \begin{pmatrix} -k & 0 & 0 \\ a\phi^j\bar{s}^j & -a(k + \psi^j + v\theta_{CF}^j) & ak\bar{Y} - a\bar{Y}\phi^j - \phi^j \\ 0 & 0 & -\phi^j \end{pmatrix}.$$

There are three eigenvalues of the matrix A_1: $\lambda_1 = -k$, $\lambda_2 = -a(k+\psi^j+v\theta_{CF}^j)$, $\lambda_3 = -\phi^j$. The expected value of $X_{t+\tau}$ is then given as

$$\operatorname{E}_t(X_{t+\tau}) = \Phi(\tau)X_t + \int_t^\tau \Phi(\tau - s)A_0 ds, \tag{5.57}$$

where $\Phi(\tau) = U\exp(\Delta\tau)U^{-1}$, and U is the matrix of eigenvectors and $\exp(\Delta\tau)$ is the diagonal matrix with diagonal elements equal to $\exp(\Delta\tau)_{ii} = e^{\lambda_i \tau}$. It follows that

$$\operatorname{E}_t\left[\int_t^\infty e^{\rho(\tau-t)} q_\tau^j d\tau\right] = \int_0^\infty e^{-\rho\tau} e_2 \Phi(\tau) X_t d\tau + \int_0^\infty e^{-\rho\tau} \int_0^\tau e_2\Phi(\tau - s)A_0 ds d\tau \tag{5.58}$$

Solving the integrals from equation (5.58) leads to

$$\operatorname{E}_t\left[\int_t^\infty e^{\rho(\tau-t)} q_\tau^j d\tau\right] = \zeta_0^j + \zeta_1^j s_t^j + \zeta_2^j s_t^j Y_t + \zeta_3^j Y_t, \tag{5.59}$$

where

$$\zeta_0^j = \frac{a\phi^j \bar{s}^j \bar{Y} k}{\alpha_0}\left[\frac{1}{\phi^j} - \frac{1}{k} + \frac{1}{\phi^j(\phi^j+\rho)} - \frac{1}{k(k+\rho)}\right] + \frac{\phi^j \bar{s}^j}{\rho}\left[-\frac{\alpha_0}{\alpha_1} + \frac{\alpha_1}{\alpha_0\alpha_3} - \frac{\alpha_1}{\phi^j(\phi^j+\rho)\alpha_0}\frac{1}{\rho^2} + \frac{\alpha_1}{\alpha_3\alpha_0(-(\rho+\alpha_3))} + \frac{1}{\rho^2}\right] \tag{5.60}$$

$$\zeta_1^j = \frac{\alpha_1}{\alpha_0}\left(\frac{1}{\rho+\phi^j} - \frac{1}{\rho}\left(\frac{\alpha_1}{\alpha_0} - 1\right)\right) - \frac{1}{\alpha_3}\frac{\alpha_1}{\alpha_0} + \frac{2}{\rho} \tag{5.61}$$

$$\zeta_2^j = \frac{1}{\rho+\phi^j} - \frac{1}{\rho}\left(\frac{\alpha_1}{\alpha_0} - 1\right) \tag{5.62}$$

$$\zeta_3^j = \frac{a\phi^j \bar{s}^j \bar{Y} k}{\alpha_0}\left(\frac{1}{\rho+\phi^j} - \frac{1}{\rho+k}\right) \tag{5.63}$$

and

$$\alpha_0 = ak - k + a\phi^j + av\theta_{CF}^j \tag{5.64}$$

$$\alpha_1 = \phi^j - ak\bar{Y} + a\lambda v\theta_{CF}^j + a\phi^j \bar{s}^j \bar{Y} \tag{5.65}$$

$$\alpha_2 = a(k + \phi^j + v\theta_{CF}^j). \tag{5.66}$$

The closed-form solution for price of the risky asset j is then given by

$$P_t^j(Y_t, s_t^j) = C_t g_t^{-1}(\zeta_0^j + \zeta_1^j s_t^j + \zeta_2^j s_t^j Y_t + \zeta_3^j Y_t). \tag{5.67}$$

□

Proof of Proposition 7

Proof. Itô's lemma to the equilibrium price equation of the risky asset j from Proposition 6 yields

$$\frac{dP_t^j}{P_t^j} = \frac{\partial P_t^j}{\partial C_t}dC_t + +\frac{\partial P_t^j}{\partial s_t^j}ds_t^j + \frac{\partial P_t^j}{\partial Y_t}dY_t + \frac{1}{2}\frac{\partial^2 P_t^j}{\partial Y_t^2}(dY_t)^2 + \frac{\partial^2 P_t^j}{\partial C_t Y_t}dC_t dY_t + \frac{\partial^2 P_t^j}{\partial C_t s_t^j}dC_t ds_t^j + \frac{\partial^2 P_t^j}{\partial s_t^j Y_t}ds_t^j dY_t. \tag{5.68}$$

I collect all the diffusion terms to get

$$\sigma_R^j(Y_t, s_t^j) = \sigma_C(Y_t) - (\gamma_1^j - \frac{a}{g_t})\sigma_C(Y_t)Y_t + \gamma_2^j \sigma^j(s_t)s_t^j. \tag{5.69}$$

□

Proof of Proposition 9

Proof. The conditional β^j is defined as

$$\beta^j(Y_t, s_t^j) = \frac{\text{cov}_t(r_t^j, r_t^m)}{\text{var}_t(r_t^m)} = \frac{\sigma_R^j(Y_t, s_t^j)\sigma_R(Y_t)'}{\sigma_R(Y_t)\sigma_R(Y_t)'} \tag{5.70}$$

Combining the information from Proposition 4 and 7 leads to

$$\beta^j(Y_t, s_t^j) = \frac{\sigma_C(Y_t) - \left(\gamma_1^j(\theta_{CF}^j) - \frac{a}{g_t}\right) v\sigma_C(Y_t)Y_t + \gamma_2^j(\theta_{CF}^j)\sigma^j(s_t)s_t^j}{\left(1 + \frac{aY_t}{g_t}\frac{kv}{(\rho a(Y_t - \bar{Y}) + \rho + k)}\right)\sigma_C(Y_t)}. \tag{5.71}$$

□

Proof of Proposition 10

Proof. It follows from the definitions of $\sigma_R^j(Y_t, s_t^j)$ and $\sigma_R(Y_t)$ that

$$\sigma_R^j(Y_t, s_t^j)\sigma_R(Y_t)' = \left(1 + \frac{\partial P_t^j}{\partial Y_t}\frac{Y_t}{P_t^j}(-v\sigma_C(Y_t)) + \frac{\partial P_t^j}{\partial s_t^j}\frac{s_t^j}{P_t^j}\sigma^j(s_t)\right)\sigma_C(Y_t) \tag{5.72}$$

and

$$\sigma_R(Y_t)\sigma_R(Y_t)' = \left(1 + \frac{\partial P_t}{\partial Y_t}\frac{Y_t}{P_t}(-v\sigma_C(Y_t))\right)^2 \sigma_C(Y_t)\sigma_C(Y_t)' \tag{5.73}$$

The conditional β^j from Proposition 9 can now be decomposed into two components.

$$\beta^j(s_t^j, Y_t) = \underbrace{\frac{\frac{\partial P_t^j}{\partial s_t^j}\frac{s_t^j}{P_t^j}\sigma^j(s_t)}{1 + \frac{\partial P_t}{\partial Y_t}\frac{Y_t}{P_t}(-v\sigma_C(Y_t))}}_{\beta_{CF}^j} + \underbrace{\frac{1 + \frac{\partial P_t^j}{\partial Y_t}\frac{Y_t}{P_t^j}(-v\sigma_C(Y_t))}{1 + \frac{\partial P_t}{\partial Y_t}\frac{Y_t}{P_t}(-v\sigma_C(Y_t))}}_{\beta_{DISC}^j}, \tag{5.74}$$

where the first component refers to the sensitivity of return covariance to shocks in the consumption share (s_t^j) and the second component describes the sensitivity of return covariance to changes in the state variable (Y_t). I derive the equilibrium cash-flow beta and the discount-rate beta to be

$$\beta_{CF}^j(s_t^j, Y_t) = \frac{\gamma_2^j(\theta_{CF}^j)s_t^j\sigma^j(s_t)}{\sigma_C(Y_t) + akv\frac{\sigma_C(Y_t)Y_t}{g_t(\rho a(Y_t - \bar{Y}) + \rho + k)}}. \tag{5.75}$$

and

$$\beta_{DISC}^j(s_t^j, Y_t) = \frac{\sigma_C(Y_t) - \left(\gamma_1^j(\theta_{CF}^j) - \frac{a}{g_t}\right) v\sigma_C(Y_t)Y_t}{\sigma_C + akv\frac{\sigma_C(Y_t)Y_t}{g_t(\rho a(Y_t - \bar{Y}) + \rho + k)}}. \tag{5.76}$$

□

6

Conclusion

This thesis contributes to widen the understanding of the cross-sectional asymmetric dependence between equity returns and market returns. It compares the cross section of stock returns across the worlds 38 largest stock exchanges with particular emphasis on the importance of asymmetric dependence for international investors. In this thesis, I find that asymmetric dependence is consistently priced in international equity returns. Indeed, asymmetric dependence is the only factor that is priced in all the in-sample regressions and the vast majority of my out-of-sample regressions.

I provide evidence that changes in AD are related to the growth of financial markets relative to GDP and the conditions necessary for the establishment of a business enterprise. In particular, the degree of asymmetric dependence rises in countries with increasing market capitalization to GDP. This suggests that the growth in size and importance of financial markets have negative effects that may influence the stability of these markets, as well as the economy as a whole. Moreover, investors become more sensitive to asymmetric dependence and require a higher additional return premium to bear asymmetric dependence risk in countries with a high change in market capitalization to GDP.

I also study the existence of asymmetric dependence among US Real-Estate

Investment Trusts (REITs). REITs are generally considered to have a low correlation with the market, which provides desirable diversification qualities. I provide new evidence that shows that these diversification benefits are diminished for most of US REITs because of existence of the lower-tail asymmetric dependence. I also quantify investor sensitivity to this asymmetric dependence in the US REITs market. I find a strong empirical evidence that AD in US REIT returns are related with a significant price.

Last but not least, I examine how fundamental cash-flow risk of firms affects the cross-sectional asymmetric dependence between stock and market returns. I find that portfolios with high fundamental cash-flow risk are likely to perform the worst during bad economic conditions because they exhibit a relatively high degree of asymmetric dependence.

I develop a consumption-based general equilibrium model with investors experiencing preference shocks that are exposed to heterogeneous cash-flow risks of assets. The model predicts that during periods associated with negative consumption shocks, assets with a low cash-flow risk will perform relatively better. In contrast, high cash-flow risk stocks are shown to exhibit a higher degree of asymmetric dependence.

This thesis has important implications for the understanding of the time-varying risk profile of firms and their cost-of-capital estimation. I show that firms with a high level of fundamental cash-flow risk are likely to have largely volatile CAPM β, which complicates the capital allocation process that is based on assessing future risk profiles of investments. It is important to be particularly careful when making investment decisions in firms with a high covariance of cash-flow growth and aggregate consumption growth because these firms are shown to exhibit a relatively higher degree of asymmetric dependence and are likely to substantially underperform relative to other assets during market downturns.

References

Jamie Alcock and Anthony Hatherley. Asymmetric dependence between domestic equity indices and its effect on portfolio construction. *Australian Actuarial Journal*, 15(1):143–180, 2009. 57

Jamie Alcock and Anthony Hatherley. Characterizing the asymmetric dependence premium. *Review of Finance*, 21(4):1701–1737, 2016. 2, 4, 6, 7, 8, 9, 11, 18, 20, 21, 22, 23, 59, 84, 126, 127, 128, 129, 130

Jamie Alcock and Eva Steiner. Fundamental drivers of dependence in REIT returns. *Available at SSRN: http://ssrn.com/abstract=2669101*, 2015. 58

Jamie Alcock, John Glascock, and Eva Steiner. Manipulation in US REIT investment performance evaluation: Empirical evidence. *The Journal of Real Estate Finance and Economics*, 47(3):434–465, 2013. 58

Yakov Amihud. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56, 2002. 21, 31, 34, 53, 55

Yakov Amihud, Allaudeen Hameed, Wenjin Kang, and Huiping Zhang. The illiquidity premium: International evidence. *Journal of Financial Economics*, 117 (2):350–368, 2015. 20, 24, 27, 34, 45

Heng An, William Hardin, and Zhonghua Wu. Information asymmetry and corporate liquidity management: Evidence from real estate investment trusts. *The Journal of Real Estate Finance and Economics*, 45(3):678–704, 2012. 59

Heng An, Qun Wu, and Zhonghua Wu. REIT crash risk and institutional investors. *The Journal of Real Estate Finance and Economics*, pages 1–32, 2015. 73

Andrew Ang and Geert Bekaert. International asset allocation with regime shifts. *Review of Financial studies*, 15(4):1137–1187, 2002. 1, 6, 57

Andrew Ang and Joseph Chen. Asymmetric correlations of equity portfolios. *Journal of Financial Economics*, 63(3):443–494, 2002. 7, 10, 30, 57

Andrew Ang, Joseph Chen, and Yuhang Xing. Downside risk. *Review of Financial Studies*, 19(4):1191–1239, 2006a. 2, 7, 11, 13, 16, 21, 31, 33, 57, 62, 65, 67, 68, 75, 82, 83, 84, 88, 89, 91

Andrew Ang, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang. The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1):259–299, 2006b. 1, 6, 127

Turan G Bali, K Ozgur Demirtas, and Haim Levy. Is there an intertemporal relation between downside risk and expected returns? *Journal of Financial and Quantitative Analysis*, 44(04):883–909, 2009. 57

Susanto Basu and Brent Bundick. Uncertainty shocks in a model of effective demand. *Econometrica*, 85(3):937–958, 2017. 100

Thorsten Beck, Asli Demirgüç-Kunt, and Ross Levine. Law and finance: Why does legal origin matter? *Journal of Comparative Economics*, 31(4):653–675, 2003. 38

Geert Bekaert, Robert J Hodrick, and David A Marshall. On biases in tests of the expectations hypothesis of the term structure of interest rates. *Journal of Financial Economics*, 44(3):309–348, 1997. 14

David A Belsley. A guide to using the collinearity diagnostics. *Computer Science in Economics and Management*, 4(1):33–50, 1991. 64

Daniele Bianchi and Massimo Guidolin. Can linear predictability models time bull and bear real estate markets? Out-of-sample evidence from REIT portfolios. *The Journal of Real Estate Finance and Economics*, 49(1):116–164, 2014. 57, 59

Tim Bollerslev and Viktor Todorov. Tails, fears, and risk premia. *The Journal of Finance*, 66(6):2165–2211, 2011. 57

Tim Bollerslev, Robert F Engle, and Jeffrey M Wooldridge. A capital asset pricing model with time-varying covariances. *The Journal of Political Economy*, pages 116–131, 1988. 23

Theodore Bos and Paul Newbold. An empirical investigation of the possibility of stochastic systematic risk in the market model. *Journal of Business*, pages 35–41, 1984. 23

Michael Bradley, Dennis R Capozza, and Paul J Seguin. Dividend policy and cash-flow uncertainty. *Real Estate Economics*, 26(4):555–580, 1998. 59

Douglas T Breeden, Michael R Gibbons, and Robert H Litzenberger. Empirical tests of the consumption-oriented capm. *The Journal of Finance*, 44(2):231–262, 1989. 116

Arturo Bris, William N Goetzmann, and Ning Zhu. Efficiency and the bear: Short sales and markets around the world. *The Journal of Finance*, 62(3):1029–1079, 2007. 52

John Y Campbell and John H Cochrane. By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2):205–251, 1999. 97

John Y Campbell and Motohiro Yogo. Efficient tests of stock return predictability. *Journal of financial economics*, 81(1):27–60, 2006. 69

John Y Campbell, Martin Lettau, Burton G Malkiel, and Yexiao Xu. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance*, 56(1), 2001. 66

Rachel Campbell, Kees Koedijk, and Paul Kofman. Increased correlation in bear markets. *Financial Analysts Journal*, 58(1):87–94, 2002. 1, 6

Brad Case, William G Hardin, and Zhonghua Wu. REIT dividend policies and dividend announcement effects during the 2008–2009 liquidity crisis. *Real Estate Economics*, 40(3):387–421, 2012a. 59, 74

Bradford Case, Yawei Yang, and Yildiray Yildirim. Dynamic correlations among asset classes: REIT and stock returns. *The Journal of Real Estate Finance and Economics*, 44(3):298–318, 2012b. 57

Fousseni Chabi-Yo, Stefan Ruenzi, and Florian Weigert. Crash sensitivity and the cross-section of expected stock returns. *Forthcoming. Journal of Financial and Quantitative Analysis*, 2017. 1, 6, 128

Kakeung C Chan, G Andrew Karolyi, and RenéM Stulz. Global financial markets and the risk premium on us equity. *Journal of Financial Economics*, 32(2): 137–167, 1992. 20

Kam C Chan, Patric H Hendershott, and Anthony B Sanders. Risk and return on real estate: evidence from equity REITs. *Real Estate Economics*, 18(4):431–452, 1990. 57

Arjun Chatrath, Youguo Liang, and Willard McIntosh. The asymmetric REIT-beta puzzle. *Journal of Real Estate Portfolio Management*, 6(2):101–111, 2000. 57

Stevenson Simon Chong, James and Jolle Miffre. Conditional correlations and Real Estate Investment Trusts. *Journal of Real Estate Portfolio Management*, 15(2):173–184, 2009. 57, 59

Tarun Chordia, Richard Roll, and Avanidhar Subrahmanyam. Commonality in liquidity. *Journal of Financial Economics*, 56(1):3–28, 2000. 45

Jim Clayton and Greg MacKinnon. The relative importance of stock, bond and real estate factors in explaining REIT returns. *The Journal of Real Estate Finance and Economics*, 27(1):39–60, 2003. 57

Kent Daniel and David Marshall. Equity-premium and risk-free-rate puzzles at long horizons. *Macroeconomic Dynamics*, 1(2):452–484, 1997. 117

Kent Daniel and Sheridan Titman. Evidence on the characteristics of cross sectional variation in stock returns. *The Journal of Finance*, 52(1):1–33, 1997. 32

Prashant K Das, Julia Freybote, and Gianluca Marcato. An investigation into sentiment-induced institutional trading behavior and asset pricing in the REIT market. *The Journal of Real Estate Finance and Economics*, pages 1–30, 2015. 73

Erik Devos, Seow-Eng Ong, Andrew C Spieler, and Desmond Tsang. REIT institutional ownership dynamics and the financial crisis. *The Journal of Real Estate Finance and Economics*, 47(2):266–288, 2013. 74

Douglas W Diamond and Raghuram G Rajan. The credit crisis: Conjectures about causes and remedies. *The American Economic Review*, 99(2):606, 2009. 58

Simeon Djankov, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. The regulation of entry. *Quarterly Journal of Economics*, pages 1–37, 2002. 38

Simeon Djankov, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. Courts. *The Quarterly Journal of Economics*, pages 453–517, 2003. 38

Simeon Djankov, Caralee McLiesh, and Andrei Shleifer. Private credit in 129 countries. *Journal of Financial Economics*, 84(2):299–329, 2007. 38

Simeon Djankov, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. The law and economics of self-dealing. *Journal of Financial Economics*, 88(3): 430–465, 2008. 38

Simeon Djankov, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. Disclosure by politicians. *American Economic Journal: Applied Economics*, 2 (2):179–209, 2010. 52

Larry G Epstein and Stanley E Zin. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. *Journal of political Economy*, 99(2):263–286, 1991. 99

Larry G Epstein and Stanley E Zin. The independence axiom and asset returns. *Journal of Empirical Finance*, 8(5):537–572, 2001. 14

Claude B Erb, Campbell R Harvey, and Tadas E Viskanta. Forecasting international equity correlations. *Financial Analysts Journal*, 50(6):32–45, 1994. 57

Claude B Erb, Campbell R Harvey, and Tadas E Viskanta. Political risk, economic risk, and financial risk. *Financial Analysts Journal*, 52(6):29–46, 1996. 19, 38

Frank J Fabozzi and Jack Clark Francis. Beta as a random coefficient. *Journal of Financial and Quantitative Analysis*, 13(01):101–116, 1978. 23

Eugene F Fama and Kenneth R French. The cross-section of expected stock returns. *the Journal of Finance*, 47(2):427–465, 1992. 34

Eugene F Fama and Kenneth R French. Value versus growth: The international evidence. *The Journal of Finance*, 53(6):1975–1999, 1998. 20, 34

Eugene F Fama and Kenneth R French. Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3):457–472, 2012. 20, 34

Eugene F Fama and Kenneth R French. International tests of a five-factor asset pricing model. *Journal of financial Economics*, 123(3):441–463, 2017. 20, 34

Eugene F Fama and James D MacBeth. Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, pages 607–636, 1973. 30, 31, 62, 63, 66, 82, 83, 90, 92

Pablo Fernandez, Pablo Linares, and Isabel Fernández Acín. Market risk premium used in 88 countries in 2014: A survey with 8,228 answers. *Available at SSRN 2450452*, 2014. 67

Wayne E Ferson and Campbell R Harvey. The variation of economic risk premiums. *Journal of Political Economy*, pages 385–415, 1991. 19, 23, 38

Wayne E Ferson and Campbell R Harvey. The risk and predictability of international equity returns. *Review of Financial Studies*, 6(3):527–566, 1993. 23

Wayne E Ferson and Campbell R Harvey. Sources of risk and expected returns in global equity markets. *Journal of Banking & Finance*, 18(4):775–803, 1994. 38

Wayne E Ferson and Robert A Korajczyk. Do arbitrage pricing models explain the predictability of stock returns? *Journal of Business*, pages 309–349, 1995. 23

Fangjian Fu. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, 91(1):24–37, 2009. 66

Christian Genest, Michel Gendron, and Michaël Bourdeau-Brien. The advent of copulas in finance. *The European Journal of Finance*, 15(7-8):609–618, 2009. 7, 34

Chinmoy Ghosh and CF Sirmans. Board independence, ownership structure and performance: evidence from real estate investment trusts. *The Journal of Real Estate Finance and Economics*, 26(2-3):287–318, 2003. 58

John Glascock and William Hughes. NAREIT identified exchange listed REITs and their performance characteristics: 1972-1991. *Journal of Real Estate Literature*, 3(1):63–83, 1995. 57

John L Glascock, David Michayluk, and Karyn Neuhauser. The riskiness of REITs surrounding the october 1997 stock market decline. *The Journal of Real Estate Finance and Economics*, 28(4):339–354, 2004. 57

William Goetzmann, Jonathan Ingersoll, Matthew Spiegel, and Ivo Welch. Portfolio performance manipulation and manipulation-proof performance measures. *Review of Financial Studies*, 20(5):1503–1546, 2007. 58

Michael A Goldstein. REIT return behavior in advancing and declining stock markets. *Real Estate Finance*, 1999. 57, 59

Simon Grant and Atsushi Kajii. AUSI expected utility: An anticipated utility theory of relative disappointment aversion. *Journal of economic behavior & organization*, 37(3):277–290, 1998. 12, 15

Simon Grant, Atsushi Kajii, and Ben Polak. Different notions of disappointment aversion. *Economics Letters*, 70(2):203–208, 2001. 12

John M Griffin. Are the Fama and French factors global or country specific? *The Review of Financial Studies*, 15(3):783–803, 2002. 5, 18, 34

Faruk Gul. A theory of disappointment aversion. *Econometrica: Journal of the Econometric Society*, pages 667–686, 1991. 12, 13, 14, 15, 16, 67, 75, 76

Philipp Hartmann, Stefan Straetmans, and Casper G De Vries. Asset market linkages in crisis periods. *Review of Economics and Statistics*, 86(1):313–326, 2004. 1, 6, 57

Campbell R Harvey. Presidential address: The scientific outlook in financial economics. *AFA*, 2017. 18

Campbell R Harvey, Yan Liu, and Heqing Zhu. ... and the cross-section of expected returns. Technical report, National Bureau of Economic Research, 2014. 18, 30, 33, 49, 60, 65, 66, 76, 78

Anthony Hatherley and Jamie Alcock. Portfolio construction incorporating asymmetric dependence structures: A user's guide. *Accounting & Finance*, 47(3): 447–472, 2007. 57

Matthew D Hill, G Wayne Kelly, and William G Hardin III. Market value of REIT liquidity. *The Journal of Real Estate Finance and Economics*, 45(2):383–401, 2012. 73

Martin Hoesli and Kustrim Reka. Volatility spillovers, comovements and contagion in securitized real estate markets. *The Journal of Real Estate Finance and Economics*, 47(1):1–35, 2013. 57

Yongmiao Hong, Jun Tu, and Guofu Zhou. Asymmetries in stock returns: Statistical tests and economic evaluation. *Review of Financial Studies*, 20(5):1547–1581, 2007. 7, 8, 9, 22, 57, 62, 126, 127

Kewei Hou, G Andrew Karolyi, and Bong-Chan Kho. What factors drive global stock returns? *Review of Financial Studies*, 24(8):2527–2574, 2011. 20, 32

John S Howe and James D Shilling. REIT advisor performance. *Real Estate Economics*, 18(4):479–500, 1990. 57

Jing-zhi Huang and Zhaodong Ken Zhong. Time variation in diversification benefits of commodity, REITs, and TIPS. *The Journal of Real Estate Finance and Economics*, 46(1):152–192, 2013. 73, 74, 75

Meichi Huang and Chih-Chiang Wu. Economic benefits and determinants of extreme dependences between REIT and stock returns. *Review of Quantitative Finance and Accounting*, 44(2):299–327, 2015. 57, 63, 65

Szu-Yin Kathy Hung and John L Glascock. Momentum profitability and market trend: evidence from REITs. *The Journal of Real Estate Finance and Economics*, 37(1):51–69, 2008. 57

Ozgur S Ince and R Burt Porter. Individual equity return data from Thomson Datastream: Handle with care! *Journal of Financial Research*, 29(4):463–479, 2006. 27

Michael C Jensen. Agency cost of free cash flow, corporate finance, and takeovers. *Corporate Finance, and Takeovers. American Economic Review*, 76(2), 1986. 59

Lei Jiang, Ke Wu, and Guofu Zhou. Asymmetry in stock comovements: An entropy approach. *Journal of Financial and Quantitative Analysis, forthcoming*, 2017. 1

Kyle Jurado, Sydney C Ludvigson, and Serena Ng. Measuring uncertainty. *American Economic Review*, 105(3):1177–1216, 2015. 118, 119, 122, 123, 128, 129, 130, 131, 132

G Andrew Karolyi, Kuan-Hui Lee, and Mathijs A Van Dijk. Understanding commonality in liquidity around the world. *Journal of Financial Economics*, 105 (1):82–112, 2012. 27, 45

Bryan Kelly and Hao Jiang. Tail risk and asset prices. *The Review of Financial Studies*, 27(10):2841–2871, 2014. 1, 6, 128

John Knight, Colin Lizieri, and Stephen Satchell. Diversification when it hurts? The joint distributions of real estate and equity markets 1. *Journal of Property Research*, 22(04):309–323, 2005. 57, 63, 73, 74, 75

John L Knight, Stephen E Satchell, and Kien C Tran. Statistical modelling of asymmetric risk in asset returns. *Applied Mathematical Finance*, 2(3):155–172, 1995. 1, 6

Tim A Kroencke. Asset pricing without garbage. *The Journal of Finance*, 72(1): 47–98, 2017. 116, 117, 118, 122, 123, 124, 128, 129, 130, 131, 132

Kuan-Hui Lee. The world price of liquidity risk. *Journal of Financial Economics*, 99(1):136–161, 2011. 20

Martin Lettau and Sydney Ludvigson. Consumption, aggregate wealth, and expected stock returns. *the Journal of Finance*, 56(3):815–849, 2001. 118, 119, 122, 123, 128, 129, 130, 131, 132

Jonathan Lewellen and Stefan Nagel. The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics*, 82(2):289–314, 2006. 21

Donald Lien and Yaqin Wang. Risk aversion, disappointment aversion, and futures hedging. *Journal of Futures Markets*, 22(2):123–141, 2002. 16

Colin Lizieri and Stephen Satchell. Interactions between property and equity markets: An investigation of linkages in the United Kingdom 1972–1992. *The Journal of Real Estate Finance and Economics*, 15(1):11–26, 1997a. 57

Colin Lizieri and Stephen Satchell. Property company performance and real interest rates: a regime-switching approach. *Journal of Property Research*, 14(2): 85–97, 1997b. 57

Colin Lizieri, Stephen Satchell, and Qi Zhang. The underlying return-generating factors for REIT returns: an application of independent component analysis. *Real Estate Economics*, 35(4):569–598, 2007. 57

Francois Longin and Bruno Solnik. Extreme correlation of international equity markets. *Journal of Finance*, pages 649–676, 2001. 57

Rand Kwong Yew Low, Jamie Alcock, Robert Faff, and Timothy Brailsford. Canonical vine copulas in the context of modern portfolio management: Are they worth it? *Journal of Banking & Finance*, 37(8):3085–3099, 2013. 34, 57

Lior Menzly, Tano Santos, and Pietro Veronesi. Understanding predictability. *Journal of Political Economy*, 112(1):1–47, 2004. 94, 95, 102, 103, 105, 121, 137

Robert C Merton. Presidential address: A simple model of capital market equilibrium. *Journal of Finance*, 42:483–510, 1987. 66

Whitney K Newey and Kenneth D West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987a. 88, 89, 90, 91, 92

Whitney K Newey and Kenneth D West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987b. 22, 31, 63, 69, 82, 83, 84

Whitney K Newey and Kenneth D West. Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653, 1994a. 88, 89, 90, 91, 92

Whitney K Newey and Kenneth D West. Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653, 1994b. 23, 31, 63, 69, 82, 83, 84

Michel Normandin and Pascal St-Amour. Substitution, risk aversion, taste shocks and equity premia. *Journal of Applied Econometrics*, 13(3):265–281, 1998. 100

Dong Hwan Oh and Andrew J Patton. Modeling dependence in high dimensions with factor copulas. *Journal of Business & Economic Statistics*, 35(1):139–154, 2017. 1, 34

Arvind Pai and David Geltner. Stocks are from Mars, real estate is from Venus. *Journal of Portfolio Management*, page 134, 2007. 58, 60, 68

Kanak Patel and Kridsda Nimmanunta. Tail dependence in REIT returns. Technical report, European Real Estate Society (ERES), 2009. 57

Andrew J Patton. On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. *Journal of Financial Econometrics*, 2(1):130–168, 2004. 1, 6, 57

Andrew J Patton. A review of copula models for economic time series. *Journal of Multivariate Analysis*, 110:4–18, 2012. 34

Rafael La Porta, Florencio Lopez-de Silanes, Andrei Shleifer, and Robert W Vishny. Law and finance. *Journal of Political Economy*, 106(6):1113–1155, 1998. 19

Thierry Post and Pim Van Vliet. Downside risk and asset pricing. *Journal of Banking & Finance*, 30(3):823–849, 2006. 57

Ning Rong and Stefan Trück. Returns of REITs and stock markets: Measuring dependence and risk. *Journal of Property Investment & Finance*, 28(1):34–57, 2010. 57

Bryan R Routledge and Stanley E Zin. Generalized disappointment aversion and asset prices. *The Journal of Finance*, 65(4):1303–1332, 2010. 14, 15

Tano Santos and Pietro Veronesi. Conditional betas. Technical report, National Bureau of Economic Research, 2004. 97

Tano Santos and Pietro Veronesi. Habits and leverage. Technical report, National Bureau of Economic Research, 2017. 98, 102, 109

Alexi Savov. Asset pricing with garbage. *The Journal of Finance*, 66(1):177–201, 2011. 116

Steven Simon and Wing Lon Ng. The effect of the real estate downturn on the link between REITs and the stock market. *Journal of Real Estate Portfolio Management*, 15(3):211–219, 2009. 57, 59

Costis Skiadas. Conditioning and aggregation of preferences. *Econometrica*, 65 (2):347–367, 1997. 2, 12, 13, 14, 20, 32, 36, 60, 67, 68, 71, 77, 78

Libo Sun, Sheridan D Titman, and Garry J Twite. REIT and commercial real estate returns: A postmortem of the financial crisis. *Real Estate Economics*, 43 (1):8–36, 2015. 57, 72, 74

Mathijs A Van Dijk. Is size dead? A review of the size effect in equity returns. *Journal of Banking & Finance*, 35(12):3263–3274, 2011. 20

Oldrich A Vasicek. A note on using cross-sectional information in Bayesian estimation of security betas. *The Journal of Finance*, 28(5):1233–1239, 1973. 28

Akiko Watanabe, Yan Xu, Tong Yao, and Tong Yu. The asset growth effect: Insights from international equity markets. *Journal of Financial Economics*, 108(2):529–563, 2013. 20

Florian Weigert. Crash aversion and the cross-section of expected stock returns worldwide. *The Review of Asset Pricing Studies*, 6(1):135–178, 2015. 1, 6, 10, 20, 32, 34, 128

Xiaoyan Zhang. Specification tests of international asset pricing models. *Journal of International Money and Finance*, 25(2):275–307, 2006. 32

Jian Zhou and Randy I Anderson. Extreme risk measures for international REIT markets. *The Journal of Real Estate Finance and Economics*, 45(1):152–170, 2012. 73

Jian Zhou and Randy I Anderson. An empirical investigation of herding behavior in the US REIT market. *The Journal of Real Estate Finance and Economics*, 47(1):83–108, 2013. 59, 73

David M Zimmer. Asymmetric dependence in house prices: evidence from USA and international data. *Empirical Economics*, 49(1):161–183, 2015. 57