Disaster and Fortune Risk in Asset Returns

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November 2016

Abstract

Do Disaster risk and Fortune risk fetch a premium or discount in the pricing of individual assets? Disaster risk and Fortune risk are measures for the co-movement of individual stocks with the market, given that the state of the world is extremely bad and extremely good, respectively. To address this question measures of Disaster risk and Fortune risk, derived from statistical Extreme Value Theory, are constructed. The measures are non-parametric and the number of order statistics to be used in the analysis is based on the Kolmogorov-Smirnov distance. This alleviates the problem of an arbitrarily chosen extreme region. The extreme dependence measures are used in Fama-MacBeth cross-sectional asset pricing regressions including Market, Fama-French, Liquidity and Momentum factors. I find that Disaster risk fetches a significant premium of 0.34% for the average stock.

*Tinbergen Institute and the Systemic Risk Centre, London School of Economics and Political Science. I want to thank Aaditya Muthukumaran, Andre Lucas, Bjorn Jorgensen, Casper de Vries, Dirk Schoenmaker, Emil Siriwardane, John Einmahl, Jon Danielsson, Philipp Hartmann, Stijn van Nieuwerburgh and Xavier Gabaix for the valuable feedback and discussions. I also thank the seminar participants at the Duisenberg school of finance, the Erasmus University, University College London and the 10^{th} Seminar on Risk, Financial Stability and Banking of the Banco Central do Brasil. I thank the Netherlands Organisation for Scientific Research Mozaiek grant [grant number: 017.005.108] for research funding. Also, the support of the Economic and Social Research Council (ESRC) in funding the Systemic Risk Centre is gratefully acknowledged [grant number ES/K002309/1].

1 Introduction

Returns in financial markets are characterized by extreme movements (Mandelbrot, 1963, Fama, 1963 and Jansen and De Vries, 1991). It is in these extreme cases that investors are highly concerned about the performance of their portfolio. The extreme movements of the market are not always reflected equally in all individual stocks. Securities which are more sensitive to these extreme negative shocks are undesirable and therefore should sell at a discount. In this paper I propose downside and upside dependency measures, i.e. Disaster and Fortune risk respectively, which captures this risk for individual stocks. These non-parametric EVT based tail dependency measures offer a new approach to capture disaster risk and fortune risk in asset prices. I find that Disaster risk fetches a robust premium. On the upside, exposure to Fortune risk carries a discount.

Prior literature on disaster risk in asset pricing mainly focuses on theoretical models. Part of this literature includes higher moments to account for tail thickness. Samuelson (1970) as well as Harvey and Siddique (2000), consider skewness and kurtosis as the higher moments. Others, like Rietz (1988) proposes an extreme event premium to explain the equity premium puzzle. He adjusted the equity premium model by Mehra and Prescott (1985), by introducing a disaster state to the Arrow-Debreu paradigm. With the inclusion of the low probability high impact state, Rietz is able to explain the equity risk premium puzzle for a reasonable choice of parameters. Barro (2006) extends this idea to investigate the impact of disaster risk on asset pricing facts and welfare costs. He finds, as Rietz does, that the equity risk premium and the risk free rate puzzle can be explained by including disaster risk. Gabaix (2012) extends these models by adding time variability of disaster risk. He is able to explain ten asset pricing puzzles including the equity premium puzzle.

Testing these theoretical models has proven to be a challenge as extreme events are only rarely observed. Several papers attempt to overcome this challenge by studying different sources of extreme movements in asset prices. Berkman, Jacobsen, and Lee (2011), Bittlingmayer (1998) and Frey and Kucher (2000) use major political crises as a measure for disaster risk. Amihud and Wohl (2004) and Rigobon and Sack (2005) find a link between the stock market and the second Iraq war. These studies lack the full empirical analysis of the systematic compensation for extreme event risk.

In this paper I consider a novel approach. This approach employs Huang's (1992) non-parametric count measure to determine the dependence in the tail between individual stocks and the market portfolio. In essence the measure counts the number of joint excesses of the market return $R_{m,t}$ and individual stock return $R_{i,t}$ conditional on the $R_{m,t}$ being stressed at time t. This captures in a direct way the dependence given that the world is in a disaster state. This measure is not limited to the left side of the tail, i.e. disaster state. It also provides a dependence measure for an extreme up state of the world.

There are currently two other empirical approaches which attempt to measure tail risk across the market. Kelly and Jiang (2014) estimate the thickness of the tail from the daily cross-section of traded stocks. Kelly and Jiang (2014) use a fixed proportion of the higher extreme order statistics to measure the tail thickness. The day-by-day tail exponent estimate functions as the measure of disaster risk in the economy. Although this measures the cross-sectional dispersion in the lower tail, it does not directly measure disaster risk in the economy. Secondly, the use of the estimator of the tail exponent by Hill (1975) in the cross-section violates the independence assumption of the Hill estimator.

The second approach in the literature uses the information of deep out of the money (OTM) put options to capture tail risk. This approach utilizes the difference between quadratic variation and integrated variance to isolate the risk of jumps. Bollerslev and Todorov (2011) infer tail risk from the OTM put options on the S&P 500. They use EVT to scale up the risk of medium jumps to large jumps. They find that jump risk and fear of jumps accounts for two-thirds of the equity risk premium. Siriwardane (2013) utilizes the difference between OTM put and call options to isolate jump risk for individual stocks. He then sorts these into portfolios according to their jump risk to create a 'High-minus-Low' factor. Both papers find that investors demand compensation for tail risk.

An advantage of the approach offered in this paper compared to the previously proposed measures is that the proposed factors are a direct and simple measure of the relationship of the state of the world and the pay-off of the financial asset. As EVT shows, the count measure has predictive value at very high but finite levels. For this measure I refrain from using the deep OTM options, e.g. as Siriwardane (2013) and Bollerslev and Todorov (2011). OTM options can suffer from liquidity issues, especially for individual companies.

The methodology of using the dispersion in the cross-section of stock returns is an indirect way of measuring tail risk. In addition, it also violates the independence assumption of the estimator. Although the risk factors introduced in this paper are simple to construct and a direct measure of the state dependence, they do have drawbacks. A limitation of using the EVT framework is that a long time series is needed to collect sufficient tail observations for the risk measure. This prohibits the measurement of time varying disaster risk. The other two approaches do not suffer this limitation.

The count measure necessitates the choice of a threshold to determine the tail region for the joint excesses of $R_{i,t}$ and $R_{m,t}$. With these thresholds the extreme area is determined, for example $(R_{i,t} < v, R_{m,t} < w)$, where v and w are the respective thresholds. The optimal thresholds for $R_{i,t}$ and $R_{m,t}$ are univariately determined, and thus in a direct way the multi-variate extreme area is constructed. To determine the thresholds, v and w, I use a methodogy which estimates the heavyness of the tail. Bickel and Sakov (2008) employ the Kolmogorov-Smirnov (KS) test to find the optimal sub-sample bootstrap size to attain convergence of the bootstrap- and a parametric distribution. Inspired by Bickel and Sakov (2008), Danielsson, Ergun, De Haan, and De Vries (2016) propose a methodology for locating the 'start' of the tail by estimating the optimal number of order statistics for the Hill estimator. To determine the optimal number of extreme order statistics they use a horizontal distance measure that minimizes the maximum distance between the empirical and the semi-parametric distribution. Given these thresholds I determine my dependence measures for the tail region.

The extreme dependence measures are employed in Fama-MacBeth regressions to determine whether they are priced and subsequently whether they fetch a premium or a discount. Disaster and Fortune risk loadings are included in the CAPM- and Fama-French factor model. The Momentum factor by Carhart (1997) and the Liquidity factor by Stambaugh and Lubos (2003) along with variables which are commonly used in the asset pricing literature are also included in the analysis. The up- and downside beta of the non-linear beta model by Ang, Chen, and Xing (2006) are included as well. The Disaster and Fortune risk measures are also utilized to test for a further non-linearisation of their model.

The results from the cross-sectional analysis indicate that high dependence in the tail of the distribution matters, especially for the downside. I find that investors demand a risk premium of 0.34% on the average stock for dependence in the downside tail region. This is in line with the results of Kelly and Jiang (2014) and Siriwardane (2013) who also find higher compensation for downside sensitivity. Further investigation reveals that Disaster risk is especially important for financial firms through a higher risk premia and a higher factor loading. Disaster and Fortune risk furthermore performs well as a further non-linearisation of the up and down beta framework by Ang et al. (2006). This indicates that a further non-linearisation is fitting for risk sensitivity of investors.

Section 2 introduces the dependence measure and discusses the asset pricing framework. This is followed by Section 3 which describes the data which is used for the empirical analyses. Section 4 presents and discusses the empirical results from the analyses, followed by the conclusion.

2 Asset pricing methodology

The methodology for asset pricing purposes consists of four parts. The first two parts elaborate on how extreme dependence is measured and how I define the start of the tail. The third part gives an overview of systematic risk measures brought forth by the literature. The fourth part elaborates on the regressions that are employed to address the question whether extreme dependence is priced in the market.

2.1 Extreme dependence measures

Investors are interested in the performance of individual stocks relative to their wealth in a particular state of the world. I examine the asset pricing in the extremely bad and extremely good states of the world. It is in these economic circumstances that investors are most sensitive to the performance of the individual stocks.

I am interested in observing extreme $R_{i,t}$ conditional on $R_{m,t}$ being extreme. The count measure which is employed in this paper is,

$$Disaster_i = \frac{\sum_{t=1}^{T} I_{\{R_{i,t}<v, R_{m,t}<w\}}}{\sum_{t=1}^{T} I_{\{R_{m,t}<w\}}} \tag{1}$$

where I is the indicator function. The summation in the numerator counts the number of paired observations which fall in the extreme quadrant, indicated in Figure 1. This measure can be viewed as the conditional probability,

$$P\left(R_{m,t} < w, R_{i,t} < v \mid R_{m,t} < w\right) = \frac{P\left(R_{m,t} < w, R_{i,t} < v\right)}{P\left(R_{m,t} < w\right)}.$$

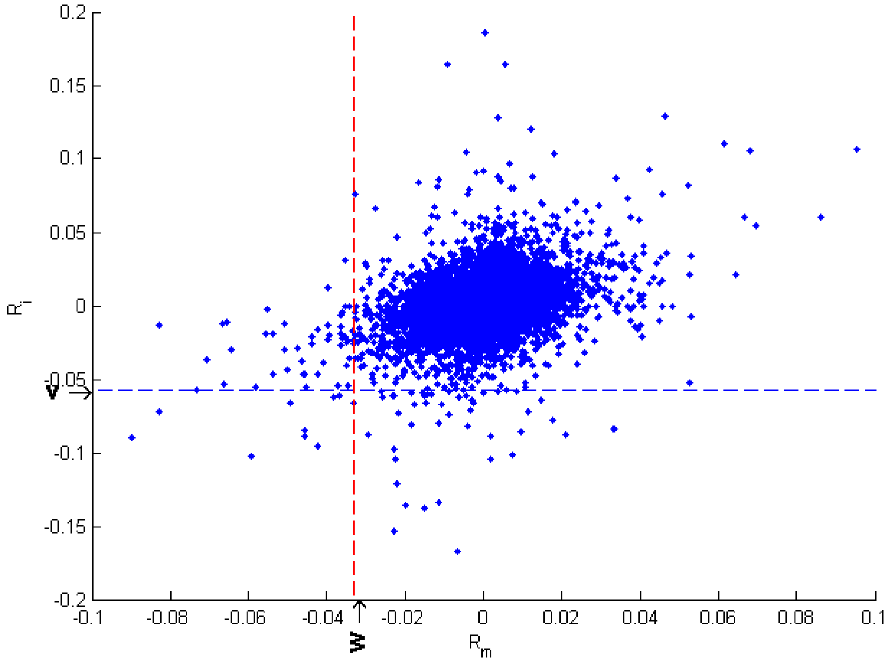

Figure 1: This graph gives the scatter plot of Allegheny Power Systems Inc. returns and the corresponding market returns. Here w is the illustrative optimal threshold level for the market returns and v is the illustrative optimal threshold level of stock i for the left tail. The region under v and to the left of w is the extreme quadrant for Disaster risk.

This dependence measure is a proxy for the level of dependence a stock has on extreme market risk. For v and w going to infinity the conditional probability tends to the tail dependence measure presented in Hartmann, Straetmans, and De Vries (2004). A thorough derivation is provided in De Haan and Ferreira (2007). Under the self-similarity property the tail dependence model can be captured by the count measure described above. The event which the count measure seeks to quantify is: Given that the market has an extreme shock, how likely is it that stock i also exhibits an extreme movement in the same direction?

2.2 Where does the tail start?

This paper employs the Extreme Value Theory (EVT) methodology to determine where the tail of a distribution is optimally measured. Through this optimization the extreme quadrants of Disaster and Fortune risk are established.

In EVT the $1/\gamma$ in the power function $Ax^{-1/\gamma}$ determines the shape of the tail. In the literature $1/\gamma$ is often referred to as the tail index. The level of $1/\gamma$ determines how many moments exist and thus how heavy the tail of the distribution is. The most popular estimator for γ is the Hill estimator,

$$\widehat{\gamma} = \frac{1}{k}\sum_{i=1}^{k}\left(\log\left(X_{n-i+1,n}\right) - \log\left(X_{n-k,n}\right)\right) \tag{2}$$

where $X_{n-i+1,n}$ is the $(i)^{th}$ largest observation (order statistic) and k is the number of observations in tail which are used for estimating $\widehat{\gamma}$. As can be seen from Equation (2) one has to choose the nuisance parameter k which determines how many extreme order statistics are used. Figure 2 shows the change in $1/\widehat{\gamma}$ as the number of order statistics included in the estimation increase.

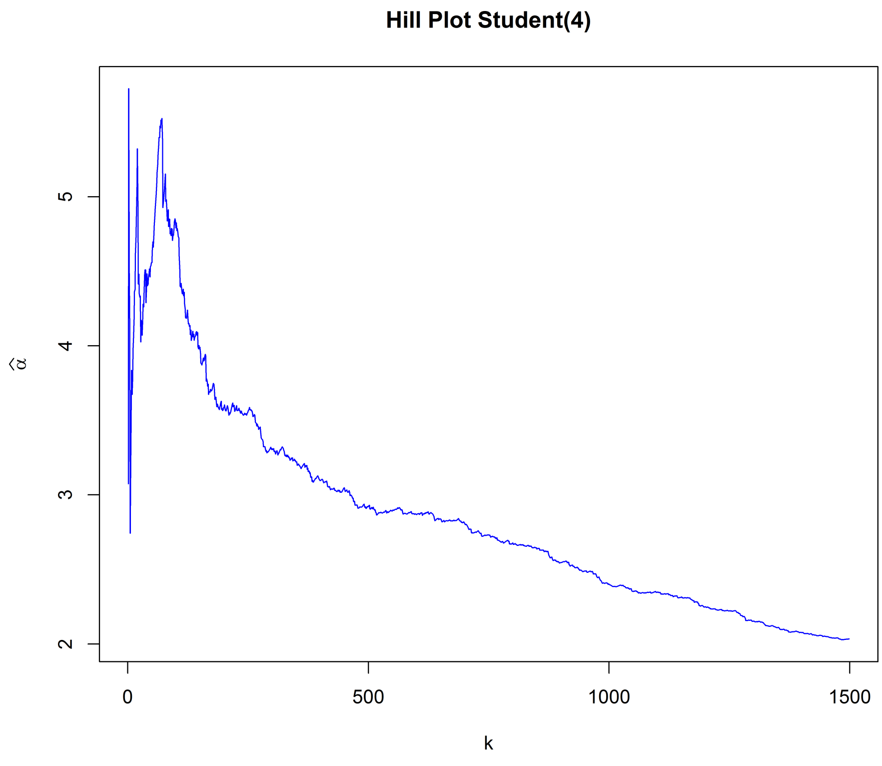

Figure 2: This graph depicts the estimate for $1/\hat{\gamma} = \hat{\alpha}$ for different levels of k. The sample of 10,000 is simulated from a Student-t distribution with 4 degrees of freedom. This graph is often referred to as the Hill plot.

To locate k^*, the optimal number of order statistics for the Hill estimator, Danielsson et al. (2016) introduce a simple method inspired by Bickel and Sakov (2008). Bickel and Sakov (2008) minimize the maximal distance between the empirical and parametric probability. They employ the Kolmogorov-Smirnov distance to match the empirical and theoretical distribution to find the optimal sub-sample size for the heavy tailed distributions. Danielsson et al. (2016) do not apply the same Kolmogorov-Smirnov metric. Instead, the distance is measured in the quantile rather than the probability dimension. The choice of the quantile dimension is motivated by the fact that a probabilistic mistake in the tail of the distribution translates into a disproportionally large quantile mismatch, which is the dimension that economists care about. Basing the metric in the quantile dimension allows them to put better emphasis on modelling the tails.

In EVT the Pareto distribution is often utilized to estimate the extreme quantiles semi-parametrically. To fit the tail one only needs estimates for the scale and tail index of the Pareto distribution. Via various simple transformations Danielsson et al. (2016) arrive at the following penalty metric,[1]

$$Q_{KS} = \inf_{1<k\leq K} \left[\sup_{1<j\leq K} \left| x_{n-j+1,n} - q\left(\frac{j}{n}\right) \right| \right].$$

I limit the area over which the above metric, i.e. KS distance metric, is measured to $x \geq X_{n-K,n}$. Here $K > k$ is large, but is still in the tail.[2] The k that produces the smallest maximum horizontal difference along all the tail observations up to K, is chosen as the optimal number of observations to estimate the thickness of the tail. Through the optimal k, i.e k^*, I also define the start of the tail.

Here I define k_i^* and k_m^* as the optimal number of order statistics in the tail which are utilized in the analysis for stock i and the market index, respectively. Once k_i^* and k_m^* are determined, I turn to the multivariate problem of measuring the dependence. From the univariate measures, k_i^* and k_m^*, an extreme dependence region is created, as in Figure 1. These regions are separately estimated for the left and right tail of the distribution.

The region $(R_{i,t} < v, R_{m,t} < w)$, where v and w correspond to the quantile of the order statistics k_i^* and k_m^* respectively, is appointed as the extreme quadrant. The number of extreme pairs of $R_{i,t}$ and $R_{m,t}$, which fall in this region, relative to the number of extreme market movements k_m^* is the dependence measure in Equation (1).

[1]See Appendix A.1 for the derivation of the semi-parametric quantile estimator.

[2]For example 10% of the sample fraction.

2.3 Other systematic risk factors

The asset pricing literature suggests several systematic risk factors. In this paper these risk factors are used as control variables. Harvey and Siddique (2000) use Coskewness as a measure of heavy tails. Coskewness is defined as

$$Coskew = \frac{E\left[\left(R_i - \mu_i\right)\left(R_m - \mu_m\right)^2\right]}{\sqrt{var\left(R_i\right)}var\left(R_m\right)},$$

where μ_i is the expected excess return of asset i and μ_m is the expected excess return on the market portfolio. Although Coskewness is not a direct measure of tail dependence, it gives an indication of a stronger relationship in the tail. Harvey and Siddique (2000) predict that lower Coskewness should be associated with higher expected returns. The estimation of Coskewness requires the full return distribution. EVT shows that only the tail observations are necessary to provide information about tail risk. Moreover, using the vast number of center observations in the estimation might create a biased measure of tail dependence.

Scott and Horvath (1980) introduce a measure of the sensitivity of the kurtosis of a stock to the market kurtosis:

$$Cokurt = \frac{E\left[\left(R_i - \mu_i\right)\left(R_m - \mu_m\right)^3\right]}{\sqrt{var\left(R_i\right)}var\left(R_m\right)^{\frac{3}{2}}}.$$

In the univariate case kurtosis is often used as an indicator for the presence of heavy tails. Cokurtosis would then be a natural extension of a measure of tail dependence. However, Cokurtosis suffers from the same drawback as the Coskewness in that it uses central observations which makes it a biased tail dependence measure. An additional problem with the Cokurtosis and Coskewness measures is that they need the second and third moment to exist. This is not always the case for financial returns.

Ang et al. (2006) propose a non-linear CAPM by separating the co-movement of an individual asset conditional on a down movement and up movement. Given that the market is above its average excess return a beta is estimated. Accordingly, this is also done for the below average state. They define the up- and downside beta as,

$$\beta^+ = \frac{cov\left(R_i, R_m | R_m > \mu_m\right)}{var\left(R_m | R_m > \mu_m\right)}$$

$$\beta^- = \frac{cov\left(R_i, R_m | R_m < \mu_m\right)}{var\left(R_m | R_m < \mu_m\right)},$$

where β^+ and β^- are the up- and downside betas, respectively.

Ang et al. (2006) winsorize the tail observations at the 99% empirical quantile for the measurement of the non-linear beta measures, β^+ and β^-. It is in my view, however, that the information lost by winsorizing provides valuable information for the extremely good and bad states of the world. I utilized the information in the winsorized observations as a further non-linearisation of their risk-return relationship. By excluding the winsorized tail observations from the up and downside beta, the tail dependence measure can be estimated using these excluded observations. Therefore, the factors proposed in this paper provide a natural extension of their framework.

2.4 Asset pricing regressions

The fourth part of the empirical methodology deals with the pricing of the factors, i.e. do investors care about Disaster and Fortune risk? These dependence measures are applied in a cross-sectional framework which is often used in the asset pricing literature.

For a first indication of whether the factors are priced in the market I start by sorting the stocks in quintiles according to the realized factor loadings.[3] The direction of the expected returns of these five portfolios indicates whether there is an initial relationship between the risk factor and expected returns.

The more formal test is a cross-sectional regression in the form of an APT framework. In this regression the newly created factors are regressed on the expected returns along with other known risk factors. The cross-sectional model has a simple linear form

$$E\left[R^e\right] = \lambda' \beta + \varepsilon$$

where $E\left[R^e\right]$ is the vector of expected returns, measured by taking the average of the monthly holding period returns of stock i. The vector of coefficients is represented by λ and can be interpreted as the risk premium. The matrix β is the factor loadings of every factor for the individual stocks. The β contains a constant, factor loading of commonly used risk factors in the literature and the extreme dependence measures developed in this paper. The ε

[3] The size of the coefficient from a regression of the stock return on the factor.

is the vector of residuals in the cross-sectional regression. The cross-sectional regressions are estimated using OLS.

Because the elements of β are estimated, an error-in-variable problem is introduced. This problem is usually overcome by using the cross-sectional framework put forth by Fama and MacBeth (1973). Alternatively, the Shanken (1992) correction can be applied. This paper uses the Fama-MacBeth procedure to alleviate the error-in-variable problem. This is a two-step procedure. An overlapping rolling window regression is utilized to estimate time varying factor loadings. In the first instance the extreme dependence measures are difficult to estimate in a rolling window framework. Due to sample size restrictions in determining the optimal threshold, there is a preference for a long time series for every asset. Requiring the sample to be long excludes short lived firms which contain essential information. Given that I apply a rolling window framework, the assets with a shorter time series will pop in and out of the rolling window. This will bias the results in the direction of a survivorship bias. To deal with this bias I perform additional robustness analyses.

In the first stage of the Fama-MacBeth procedure the factor loadings are estimated for the individual stock present in window t. This is represented as,

$$R_t^e = a_t + \beta_t X_t + \varepsilon_t$$

where R_t^e is the vector of excess returns for stock i in time window t. The X_t is a l by T matrix for the l factors and the T time units within the window t. The factor loadings are then collected in β_t. In the second stage regression the factors are tested for significance in risk premia.

$$E\left[R_t^e\right] = \lambda_t' \beta_t + \epsilon_t$$

where λ_t is the vector with the price of the risk of factors in window t.

Due to the use of the overlapping rolling windows in the Fama-MacBeth procedure, the time series of the λ are autocorrelated. To correct for this, I use Newey and West (1987) standard errors for λ.

3 Data

The analysis uses US equity market data from 1963 to 2015. The stock market data is obtained from the Center for Research in Security Prices (CRSP). The CRSP database contains individual stock data from the NYSE, AMEX, NASDAQ and NYSE Arca. The Fama-French factor (Fama and French, 1996) data is provided by the website of Kenneth R. French as is the Momentum factor by Carhart (1997). The data library contains daily and monthly constructed Fama-French and Momentum factors from 1963 to 2015. The Liquidity factor by Stambaugh and Lubos (2003) is obtained from the website of Lubos Pastor. The book-to-market ratio, which is used as one of the control variables, is obtained from the Compustat database. The Compustat database contains data from 1950 to 2015 on balance sheet items of the respective companies.

In the main analysis 19,904 stocks are included. For the data analysis the monthly stock returns need to be matched to the monthly regression factors. Therefore, the analysis is confined to the period 1963 to 2015.[4] For every stock that is included in the analysis it needs to be traded on one of the four exchanges during the entire measurement period.[5] Only stocks with more than 60 months of data are used, as accuracy of extreme value estimators typically requires a large total sample size. Only a small sample fraction is informative for tail estimation. Table 1 gives the descriptive statistics for the Disaster factor and Fortune factor.

In the Appendix, Figures 3 and 4 give additional details on the distribution of the sample fractions used for the estimation of the count measure. We see that the shape of the distribution of the k_m^* for the Disaster and Fortune risk measures are different. For the Fortune measure a relatively small percentage of the tail observations are utilized for the dependence estimation. For the Disaster risk measure we find a similar distribution of the utilized sample fraction. The fraction of market returns used does differ for the Fortune and Disaster risk measures. For Disaster risk the cut-off point of 10% of the market return observations is often used. This difference does not seem to affect the distribution of the dependence measures.

4 Empirical results

Common practice in the asset pricing literature is to sort the stocks in quintile portfolios based on their factor realizations. Subsequently, the direction of

[4]The CRSP database and Fama-French factors dataset provide information going back to 1926. For a detailed description of the construction of the Fama-French factors and the Momentum factor please visit the data library on the website of Kenneth R. French.

[5]Stocks with exchange code -2, -1 or 0 are not included in the analysis. In addition, only stocks with share code 10 and 11 are included in the analysis. Stocks with an average price below 5 dollars are ignored.

Table 1: Descriptive statistics Fortune and Disaster factor

		Fortune				Disaster			
	n	Mean	St Dev	Min	Max	Mean	St Dev	Min	Max
All	19904	0.13	0.14	0.00	0.98	0.17	0.18	0.00	0.97
Agriculture, Forestry and Mining	2971	0.09	0.10	0.00	0.69	0.12	0.14	0.00	0.82
Contractors and Construction	296	0.12	0.12	0.00	0.56	0.16	0.16	0.00	0.78
Manufacturing	7597	0.12	0.11	0.00	0.81	0.15	0.15	0.00	0.97
Transportation, Communications and Utilities	1656	0.15	0.13	0.00	0.69	0.19	0.18	0.00	0.94
Wholesale Trade	975	0.11	0.11	0.00	0.81	0.15	0.16	0.00	0.97
Retail Trade	1318	0.12	0.11	0.00	0.69	0.15	0.14	0.00	0.76
Finance, Insurance and Real Estate	5980	0.17	0.19	0.00	0.98	0.21	0.22	0.00	0.97
Business and Personal Services	2422	0.11	0.10	0.00	0.71	0.15	0.14	0.00	0.88
Health Services	437	0.09	0.10	0.00	0.57	0.13	0.15	0.00	0.81
Legal, Education and Social Services	134	0.11	0.11	0.00	0.54	0.12	0.13	0.00	0.58
Engineering, Architecture and Accounting services	496	0.11	0.10	0.00	0.57	0.17	0.16	0.00	0.86
Government (Public Administration)	57	0.17	0.22	0.00	0.93	0.19	0.16	0.00	0.66

This table displays the distributional characteristics of Depression and Fortune risk factors for all the assets and per industry. The industries are arranged according to sic codes. The first column reports the number of companies which are included in a industry. Columns 2-5 report the mean, standard deviation, maximum and minimum of the Fortune factor realizations, respectively. The columns 6-9 report the same statistics, but for the Depression factor realizations. The data includes all the securities in the CRSP universe from 1963 till 2015.

the aggregated portfolio returns is examined for the predicted relationship.

Table 2: **Single sorted portfolios** This table lists the equal-weighted average excess returns and risk characteristics of stocks sorted on extreme factor realizations. Fortune and Disaster factors are calculated using daily observations for every individual asset which is listed on NYSE, AMEX, NASDAQ or NYSE Arca in between the years 1963 and 2015. The returns on the individual assets are of a monthly frequency. The stocks within a 5 year window are all sorted in ascending order of the factor realizations. A rolling window of 5 year is used to measure the returns of the different portfolios. The column "$E(R_i^e)$" reports the average excess return of the realized factors sorted portfolio.

(a) Sorted by Disaster factors

Portfolio	$E(R_i^e)$	Fortune	Disaster
1 Low	0.1072	0.0893	0.0071
2	0.1095	0.1097	0.0423
3	0.1150	0.1234	0.1024
4	0.1181	0.1537	0.2029
5 High	0.1258	0.2075	0.4184

(b) Sorted by Fortune factors

Portfolio	$E(R_i^e)$	Fortune	Disaster
1 Low	0.1132	0.0081	0.1002
2	0.1165	0.0436	0.1242
3	0.1135	0.0928	0.1428
4	0.1186	0.1702	0.1714
5 High	0.1141	0.3715	0.2308

Table 2 shows the average returns of the lower to upper quintile portfolios sorted by the Disaster and Fortune factors. The portfolios sorted on the Disaster factor show an overall increase in the average returns. This direction is in line with the risk-return relationship that one expects. Given that the market is in an extremely bad state, if the asset is also preforming extremely badly, then investors wants to be compensated for bearing this risk by a higher expected return. The average return of the portfolios sorted on the Fortune factor are neither monotonically increasing or decreasing. One would normally expect a monotonic decline as a negative risk premium should go together with a higher frequency of large pay-offs. When observing Table 5 in the Appendix one can see that Fortune and Disaster factor loadings are positively correlated. To get a better idea of what the relationship is and how much investors want to be compensated for the exposed systematic risk follows from the Fama-MacBeth regression shown below.

Table 3: **Base case Fama-MacBeth regression**

	I	II	III	IV	V	VI
α	0.0492	0.0756	0.0498	0.0529	0.0504	0.0727
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Market	0.0622	0.0572	0.0615	0.0523	0.056	0.0561
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
SMB		2.257		2.606	2.852	2.313
		(0)***		(0)***	(0)***	(0)***
HML		-2.744		-2.819	-2.756	-2.716
		(0)***		(0)***	(0)***	(0)***
Fortune			-0.0233	-0.0099	-0.0046	0.0071
			(0.004)***	(0.079)*	(0.435)	(0.123)
Disaster			0.0201	0.0203	0.0191	0.0203
			(0.001)***	(0)***	(0)***	(0)***
Momentum		5.697			5.925	5.735
		(0)***			(0)***	(0)***
Liquidity		0.0213			0.0241	0.0215
		(0)***			(0)***	(0)***
Coskewness		0.0213				0.0182
		(0.04)**				(0.065)*
Cokurtosis		-1.283				-1.351
		(0)***				(0)***

This table shows the results of Fama-MacBeth (1973) regressions of 60-month excess returns on realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. The number of stocks in each rolling window varies from 1359 to 3371. *Market* is the CAPM beta. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. HML and SMB are high minus low and small minus big factors (Fama and French,1996) respectively. *Liquidity* is the liquidity beta by Pastor and Stambaugh (2003). *Momentum* is the momentum factor created by Carhart (1997). *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et al. (2006). The p-values for the overlapping Fama-Macbeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.

In Table 3 the CAPM and the Fama-French results are reproduced. This is the starting point for the analysis, as these are the standard results in the empirical asset pricing literature. Adding Fortune and Disaster risk to these models indicates the importance of extreme dependencies. Applying the rationale of the Arrow-Debreu framework to the Disaster risk measure would imply a positive risk premium. A stock which has extremely low returns in the extremely bad states of the world is an undesirable asset and requires a positive risk premium. When adding Disaster risk to the models the coefficient is positive and significant. This implies that investors do want to be compensated for stocks that have a high loading on Disaster risk. The premium for carrying a stock with a full loading on Disaster risk is around 2.01%. This means that a standard deviation increase of Disaster risk is a 0.4% increase in $E(R_i^e)$. These results are in line with the results of Kelly and Jiang (2014) and Siriwardane (2013).

When adding Fortune risk loadings to the cross-sectional regression the sign of the coefficient is negative. The negative sign implies a negative risk premium for having a high loading on Fortune risk, as can be seen from the third model in Table 3. The intuition behind this factor is that in the good states of the world stocks with a high loading have a tendency to pay out extremely well. This does not convey any information about the bad states of the world. As expected, investors demand a negative premium for carrying Fortune risk as assets with this risk dependence are desirable. The discount is 2.33% on an annual basis when Fortune risk is added to the standard CAPM regression. This means that a one standard deviation increase of Fortune risk implies a 0.33% decrease in $E(R_i^e)$. When added to the Fama-French factor model the premium remains negative, but becomes marginally significant. From these results one can observe that Fortune risk is priced in the parsimonious models, but looses significance as the models become more elaborate.

One can also wonder if stocks which have a high extreme dependence are sensitive to liquidity issues. Stambaugh and Lubos (2003) find that stocks with high sensitivity to liquidity have a higher expected return. This is especially a concern when the market experiences an extreme downwards movement. Model V shows that the Liquidity factor does not affect the significance of the premium on Disaster risk compared to Model IV. Fortune Risk on the other hand becomes insignificant, but has the expected sign. The Momentum factor is another addition to the APT model often applied in the asset pricing literature to account for an additional source of systematic risk. Carhart (1997) is able to explain the persistent performance of mutual funds with the Momentum factor. Adding the Momentum factor to the regression model does not significantly influence the previously found results. This implies that Disaster risk is not likely functioning as a proxy for other well tested risk factors. Given the inclusion of the Fama-French, Momentum, Liquidity, Coskewness, and Cokurtosis factor, Disaster risk is still significant and persistently has the same magnitude. Therefore, investors demand a compensation for stocks that carry Disaster risk in addition to existing risk factors.

Combining this result with the separation of the standard CAPM market factor into Ang et al. 's (2006) conditional up- and downside beta indicates that investors care differently about the co-movement in different parts of the return distribution. They show that investors want to be differently compensated for up- and downside risk. In this paper their framework is extended to include Disaster, down, up and Fortune sensitivity. The count measures are now measured at the 1% threshold level.[6] The remaining 98% of the observations are utilized to measure the up and downside beta.

The results of the second stage regressions that include these four factors are presented in Table 4. Note from Table 4 that for model III all four risk premia have the expected sign. The downside factors both fetch a premium and the upside factors exposures fetch a discount. This is consistent with the model of Ang et. al. (2006). The insignificance of β^+ is puzzling, as Fortune risk is consistently significant. This hints in the direction of a lottery behaviour of investors, i.e. only the extreme upside dependence is appreciated. The significant pricing of the extreme dependence measures indicates that investors do care about extreme co-movements above the regular co-variation in the center of the distribution. The inclusion of the σ^2 changes the regression results considerably, as seen in model V. Aside from the change in magnitude of the coefficients, the direction of the Fortune risk coefficient changes as well. The same effect is found in Ang et al. (2006), where the inclusion of σ increases the size of the constant by five times.

The correlation matrix of the factors points out that there is a correlation of 0.29 between the Disaster and Fortune risk loadings (See Table 5 in the Appendix). This might cause multicollinearity issues in the regressions of Table 3 and 4. Therefore, different robustness checks are carried out in the next section. Ang et al.'s up and downside beta loadings are relatively uncorrelated with the extreme dependence loadings. This takes away the concern that both approaches measure the same fundamental risk.

[6] I use the 1% observations, because Ang et al. (2006) winsorize their sample at 1 % and 99% level.

Table 4: **Base regression non-linear Beta model**

	I	II	III	IV	V	VI
α	1.004	0.066	0.9458	0.0686	0.0701	0.9903
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Market	0.1435					
	(0)***					
β^+		-0.0197	0.0597	-0.0106	0.0133	0.0577
		(0.001)***	(0)***	(0.08)*	(0.036)**	(0)***
β^-		0.0868	0.0697	0.0799	0.0621	0.0675
		(0)***	(0)***	(0)***	(0)***	(0)***
Fortune				-0.0885	-0.0294	0.1251
				(0)***	(0.083)*	(0)***
Disaster				0.0503	0.0596	0.1309
				(0.004)***	(0)***	(0)***
σ	-1.443		-1.177			-0.9837
	(0)***		(0)***			(0.002)***
Coskewness	-0.0941		-0.1018		-0.0791	-0.0921
	(0)***		(0)***		(0)***	(0)***
Cokurtosis	0.0006		0.0005		-0.0002	0.0005
	(0)***		(0)***		(0)***	(0)***
Bk-Mkt	0.0004		0.0003			0.0002
	(0.055)*		(0.117)			(0.227)
log(size)	-0.0541		-0.0507			-0.0546
	(0)***		(0)***			(0)***

This table shows the results of Fama and MacBeth (1973) regressions of 60-month excess returns on firm characteristics and realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. The assets have to be listed consecutively on one of the exchanges. The number of stocks in each rolling window varies from 1358 to 3468. *Market* is the CAPM beta. β^- and β^+ are the down- and upside beta (Ang et al., 2006), Respectively. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et. al. (2006). *Bk-Mkt* is the book to market ratio measured at the beginning of the rolling window. log(*size*) is the log of market capitalization, where market capitalization is measured by common shares outstanding multiplied by the share price at the beginning of the rolling window. σ is the volatility of the asset returns over the rolling window. The p-values for the overlapping Fama-MacBeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.

5 Robustness analyses

The results in Table 3 indicate that on average for the companies which have a positive exposure and have been listed for longer than 60 months a positive premia for Disaster risk is demanded. A possibility is that the sensitivity to the exposure is not equal among all firms. Table 6 shows the Fama-MacBeth regression results for stocks that are listed for longer than 180 months on one of the stock exchanges.[7] The results in Table 6 indeed indicate that regressions only applied to stocks that exist longer than 180 months have a substantially lower premium for extreme dependency than the average premium found in Table 3. This is an indication that the exposure to the extreme dependence risk factors is important for firms which are relatively young. For the more established firms extreme dependence plays a lesser role. Table 7 shows the regression results for firms which started trading on one of the exchanges from year 1997 onwards. For this subsample the results are even stronger, further supporting the higher sensitivity of younger firms to extreme dependence.

Financial firms, such as banks, are frequently highly leveraged and therefore pose challenges for linear regression frameworks. These non-linearities become apparent from Table 10 where we observe that the compensation for financial firms that load on Disaster risk is three times as high as the average compensation for non-financial firms. This result in combination with the on average higher loading on Disaster risk in the financial sector demonstrates that Disaster risk plays an important role in the risk-return relationship for firms in the financial sector.[8]

The concern might arise that the Disaster and Fortune risk perform well when the market beta is away from one and lose their explanatory power otherwise. Given that the market beta is close to unity, the origin of the extreme quadrant is more likely along the 45 degree line. Table 8 presents the results for stocks with market betas between 0.9 and 1.1. The results indicate that Disaster risk premia remains significant and positive. Fortune risk becomes insignificance under all the model specifications. This leads me to conclude that Disaster risk premia is robustly significant, as opposed to Fortune risk.

6 Conclusion

The dependence of a stock on the extreme movements of the market is an essential part for understanding the behaviour of asset prices. In these infrequent and extreme cases, investors care most about the performance of

[7] Functioning as a proxy for the maturity of the firm.

[8] See Table 1 for the average loading on Disaster risk for financial firms. Table 9 reports the Fama-MacBeth regression for non-Financial firms.

their own portfolios. In this paper a measure for the dependence of stock returns on the extreme movements of the market is created for the negative and positive extreme market movements. These measures are derived from statistical Extreme Value Theory.

The measures of Disaster and Fortune risk are subsequently applied to explain the cross-section of expected returns. This reveals whether investors care about this extreme dependence on top of other risk factors and whether extreme risk fetches a premium or a discount. The results from the cross-sectional regressions show that Disaster risk carries a premium as would be expected from theory. The premium for stocks is on average 0.34% and remains significant in various robustness checks. Investors care less about the dependence in the extreme upside. Fortune risk dependence has a negative premium, but it is not robustly significant and in some cases positive. These results are in line with the literature to date. Kelly and Jiang (2014) find that investors indeed require a discount for stocks that have high returns when tail risk is high. Ang, Chen, and Xing (2006) find in their upside and downside beta framework that there is a higher premium for the downside beta. In line with the bisection of the beta model, I proposed a further division of the risk sensitivity of the market model. I find that adding Disaster and Fortune Risk to Ang et al.'s (2006) up and downside beta forms a significant and natural extension to their model. Fortune risk and Disaster risk are significantly priced in their framework, with an average premium of 0.85% for Disaster risk and an ambiguous discount of 1.15% for Fortune risk.

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A Appendix

A.1 Quantile estimator

Suppose the tail of the distribution is regularly varying at infinity and satisfy the following expansion

$$P\left(X \leq -x\right) = F(-x) = Ax^{-\alpha}[1 + o(1)].$$

Conditional on being in the tail of the distribution, the cdf can be rewritten in the empirical counterpart

$$F_{x|x\leq -x_s}(-x) = \frac{Ax^{-\alpha_s}[1 + o(1)]}{Ax_s^{-\alpha_s}[1 + o(1)]} = \left(\frac{x}{x_s}\right)^{-\alpha_{(s)}}. \tag{3}$$

By definition

$$F_{x|x\leq -x_s}(-x) = \frac{P\left(X < x \cap X < s\right)}{F_x(-x_s)} = \frac{p}{F_x(-x_s)}. \tag{4}$$

Equating (3) and (4) gives

$$\frac{p}{F_x(-x_s)} = \left(\frac{x}{x_s}\right)^{-\alpha_{(s)}}$$

$$p = F_x(-x_s)\left(\frac{x}{x_s}\right)^{-\alpha_{(s)}}.$$

Replace $F_x(-x_s)$ by the empirical cdf and replace s by x_k and the conditioning of α on k instead of s then gives

$$p = \frac{k}{n}\left(\frac{x}{x_k}\right)^{-\alpha_{(k)}},$$

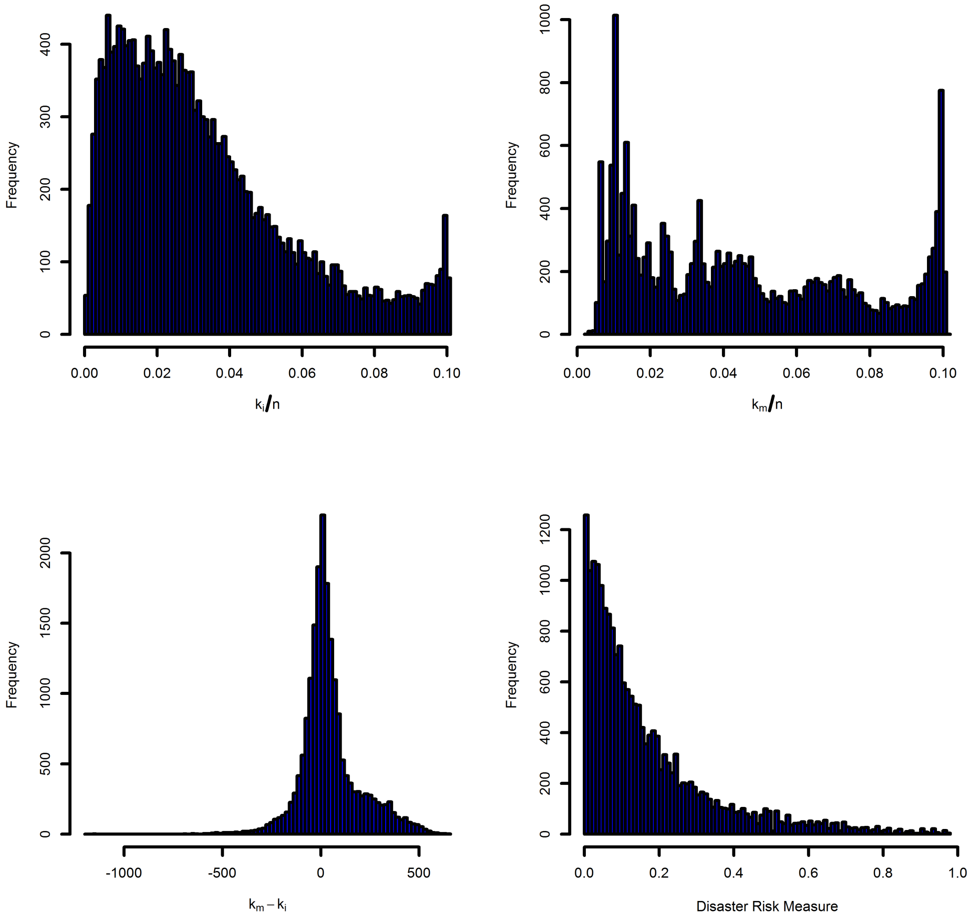
where $k = \sum I_{\{x_i < x_s\}}$ and where ${}^{k}\!/_{n}$ is the empirical cdf. Given this expression for the probability dimension, the quantile estimator $q\left({}^{j}\!/_{n}\right)$ is given by

$$q\left(\frac{j}{n}\right) = \left(\frac{k}{j}\right)^{\frac{1}{\widehat{\alpha}}k}\left(x_{k+1}\right),$$

where p is replaced by the empirical counterpart, i.e. ${}^{j}\!/_{n}$.

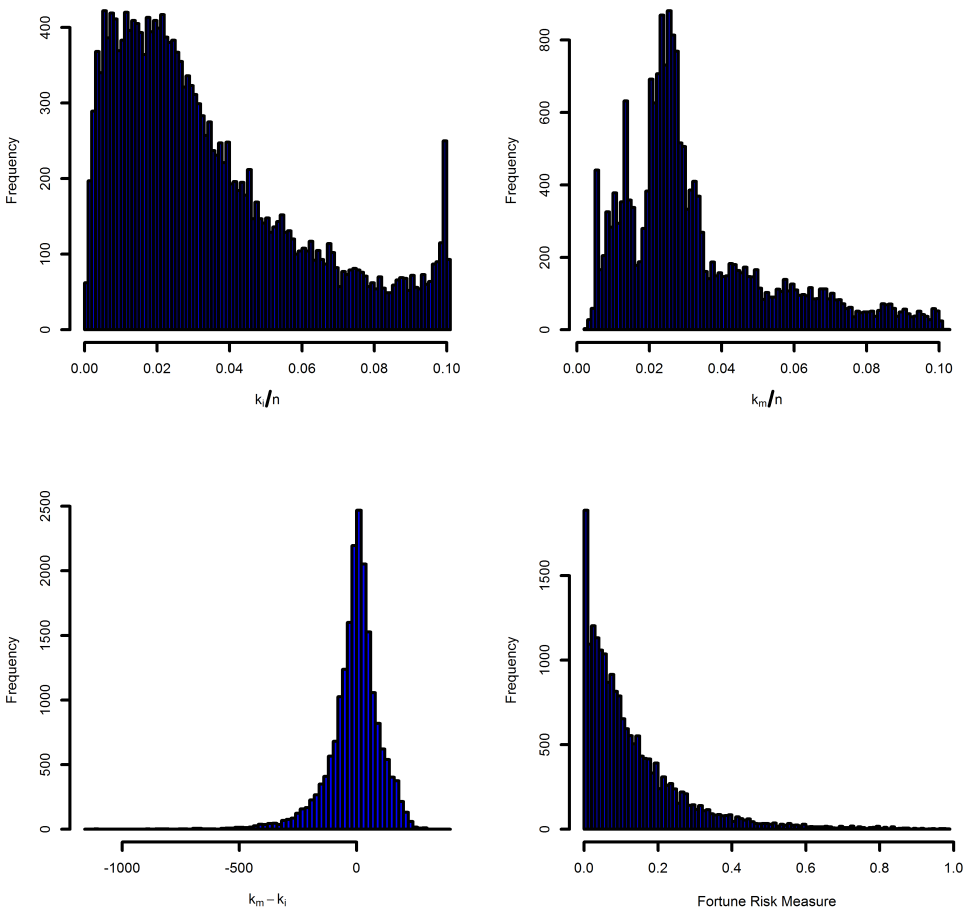
A.2 Tables and Figures

Figure 3: Characteristics Disaster risk



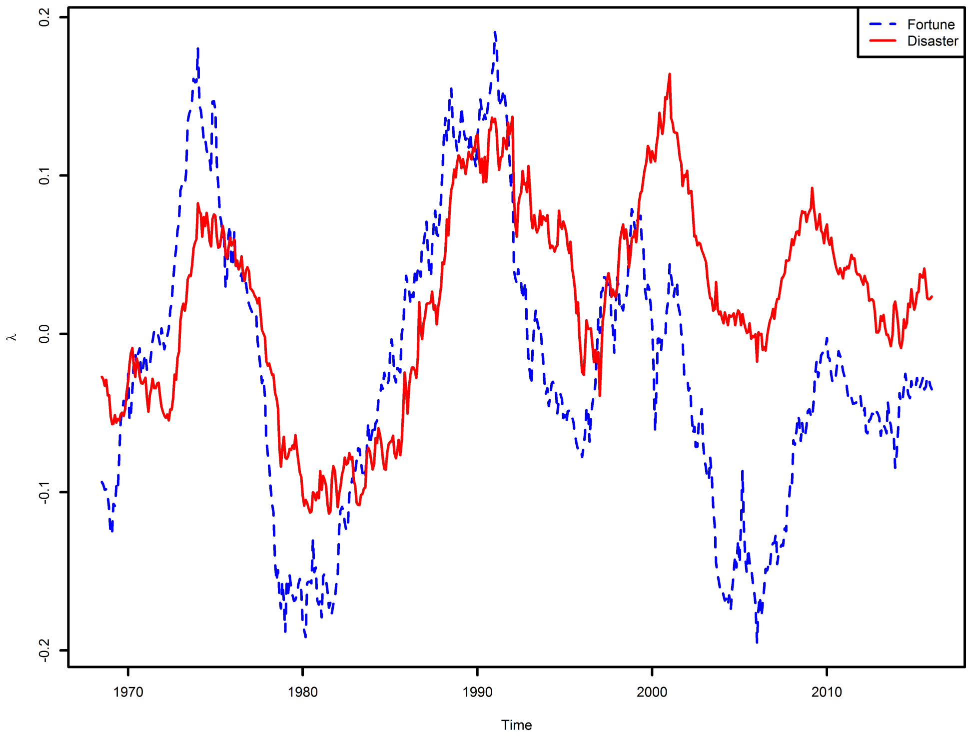
These graphs depict the distribution of the different characteristics of the Disaster measure. The upper left picture depicts the sample fraction of the total data used to define the extreme negative region of the stock. On the right you see this for the market. The lower left picture depicts the difference in the number of observations applied in the count measure for the market and stock i. The picture on the bottom right gives the distribution of the Disaster risk measure.

Figure 4: Characteristics Fortune risk



These graphs depict the distribution of the different characteristics of the Fortune measure. The upper left picture depicts the sample fraction of the total data used to define the extreme positive region of the stock. On the right you see this for the market. The lower left picture depicts the difference in the number of observations applied in the count measure for the market and stock i. The picture on the bottom right gives the distribution of the Fortune risk measure.

Figure 5: Risk premia Disaster and Fortune risk for rolling window



This graph depicts the estimated risk premia for Disaster risk and Fortune risk for every overlapping window. Here LL is the line for the Disaster factor and UR is the line for the Fortune factor. These are measures from the second stage of the overlapping window regression in the Fama-MacBeth procedure.

Table 5: **Correlation Matrix of Factor loadings**

This table describes the pairwise correlation between factor loadings that are used in this paper. The correlations shown are the average correlations measured over a five year overlapping rolling window. The number of firms included in the analysis is between1437 and 3889.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Market	1.000	0.368	0.413	0.015	0.168	0.086	0.102	-0.031	-0.225	-0.008	0.014	0.035	0.002	0.125
β^+	0.368	1.000	0.720	0.053	-0.135	0.246	0.275	-0.061	-0.085	0.042	0.087	-0.049	0.007	0.393
β^-	0.413	0.720	1.000	0.188	-0.136	0.150	0.218	-0.041	-0.033	0.132	-0.091	0.062	0.006	0.195
SMB	0.015	0.053	0.188	1.000	0.175	-0.147	-0.066	-0.071	-0.224	0.087	-0.136	0.219	-0.004	-0.312
HML	0.168	-0.135	-0.136	0.175	1.000	-0.001	-0.040	0.062	-0.129	0.027	-0.041	-0.019	-0.013	-0.039
Fortune	0.086	0.246	0.150	-0.147	-0.001	1.000	0.298	-0.012	-0.009	-0.030	0.110	-0.138	0.001	0.389
Disaster	0.102	0.275	0.218	-0.066	-0.040	0.298	1.000	-0.017	-0.010	0.020	0.076	-0.094	0.001	0.370
Momentum	-0.031	-0.061	-0.041	-0.071	0.062	-0.012	-0.017	1.000	0.055	-0.032	0.038	-0.094	-0.004	-0.047
Liquidity	-0.225	-0.085	-0.033	-0.224	-0.129	-0.009	-0.010	0.055	1.000	-0.010	-0.003	-0.006	-0.000	-0.014
Coskewness	-0.008	0.042	0.132	0.087	0.027	-0.030	0.020	-0.032	-0.010	1.000	-0.902	0.106	0.003	-0.115
Cokurtosis	0.014	0.087	-0.091	-0.136	-0.041	0.110	0.076	0.038	-0.003	-0.902	1.000	-0.140	-0.001	0.284
σ^2	0.035	-0.049	0.062	0.219	-0.019	-0.138	-0.094	-0.094	-0.006	0.106	-0.140	1.000	0.002	-0.267
Bk-Mkt	0.002	0.007	0.006	-0.004	-0.013	0.001	0.001	-0.004	-0.000	0.003	-0.001	0.002	1.000	0.009
log(size)	0.125	0.393	0.195	-0.312	-0.039	0.389	0.370	-0.047	-0.014	-0.115	0.284	-0.267	0.009	1.000

Table 6: **Firms exist for more than 180 months in the database**

	I	II	III	IV	V	VI
α	0.0505	0.0812	0.0537	0.0569	0.054	0.0794
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Market	0.0638	0.0576	0.0631	0.0518	0.0563	0.0567
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
SMB		2.514		2.936	3.172	2.54
		(0)***		(0)***	(0)***	(0)***
HML		-2.855		-3.003	-2.855	-2.812
		(0)***		(0)***	(0)***	(0)***
Fortune			-0.0364	-0.0201	-0.0153	-0.0018
			(0)***	(0)***	(0.006)***	(0.675)
Disaster			0.0156	0.0177	0.0175	0.0191
			(0.008)***	(0)***	(0)***	(0)***
Momentum		6.297			6.42	6.275
		(0)***			(0)***	(0)***
Liquidity		0.018			0.0202	0.0182
		(0)***			(0)***	(0)***
Coskewness		0.018				0.0176
		(0.04)**				(0.04)**
Cokurtosis		-1.532				-1.554
		(0)***				(0)***

This table shows the results of Fama-MacBeth (1973) regressions of 60-month excess returns on realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. The assets have to be listed consecutively on one of the exchanges for at least 180 months. The number of stocks in each rolling window varies from 1045 to 2599. *Market* is the CAPM beta. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. HML and SMB are high minus low and small minus big factors (Fama and French,1996) respectively. *Liquidity* is the liquidity beta by Pastor and Stambaugh (2003). *Momentum* is the momentum factor created by Carhart (1997). *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et al. (2006). The p-values for the overlapping Fama-Macbeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.

Table 7: **Firms which are included onto one of the exchanges after 1997**

	I	II	III	IV	V	VI
α	0.0626	0.0861	0.0524	0.0473	0.0518	0.0683
	(0)***	(0)***	(0.008)***	(0.01)***	(0.004)***	(0)***
Market	0.0728	0.0676	0.0716	0.0638	0.0625	0.0654
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
SMB		2.404		3.072	3.021	2.572
		(0)***		(0)***	(0)***	(0)***
HML		-2.405		-2.49	-2.466	-2.522
		(0.001)***		(0.001)***	(0.001)***	(0.001)***
Fortune			-0.0327	-0.0119	-0.0191	-0.0053
			(0.032)**	(0.481)	(0.167)	(0.706)
Disaster			0.0588	0.0662	0.0669	0.0737
			(0)***	(0)***	(0)***	(0)***
Momentum		1.104			1.264	1.226
		(0.299)			(0.248)	(0.256)
Liquidity		0.0182			0.0201	0.0181
		(0.029)**			(0.015)**	(0.028)**
Coskewness		-0.029				-0.0552
		(0.296)				(0.064)*
Cokurtosis		-2.262				-2.588
		(0)***				(0)***

This table shows the results of Fama-MacBeth (1973) regressions of 60-month excess returns on realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. The assets have to be listed for the first time after 1997. The number of stocks in each rolling window varies from 60 to 1282. *Market* is the CAPM beta. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. HML and SMB are high minus low and small minus big factors (Fama and French,1996) respectively. *Liquidity* is the liquidity beta by Pastor and Stambaugh (2003). *Momentum* is the momentum factor created by Carhart (1997). *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et al. (2006). The p-values for the overlapping Fama-Macbeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.

Table 8: **Firms which have a *Market* estimate between 0.9 and 1.1**

	I	II	III	IV	V	VI
α	0.0425	0.0802	0.0426	0.0517	0.056	0.0787
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Market	0.0638	0.0455	0.0617	0.0481	0.0455	0.0429
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
SMB		2.011		2.652	2.672	1.994
		(0)***		(0)***	(0)***	(0)***
HML		-3.188		-3.475	-3.148	-3.149
		(0)***		(0)***	(0)***	(0)***
Fortune			-0.0144	-0.0038	0.0009	0.0071
			(0.15)	(0.591)	(0.897)	(0.216)
Disaster			0.0228	0.0251	0.0223	0.0245
			(0)***	(0)***	(0)***	(0)***
Momentum		7.119			7.358	7.153
		(0)***			(0)***	(0)***
Liquidity		0.0125			0.019	0.0126
		(0.021)**			(0.001)***	(0.019)**
Coskewness		0.0362				0.034
		(0.012)**				(0.016)**
Cokurtosis		-0.8221				-0.9123
		(0.001)***				(0)***

This table shows the results of Fama-MacBeth (1973) regressions of 60-month excess returns on realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. Only the assets with a coefficient for *Market* between 0.9 and 1.1 are included. The number of stocks in each rolling window varies from 171 to 655. *Market* is the CAPM beta. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. HML and SMB are high minus low and small minus big factors (Fama and French,1996) respectively. *Liquidity* is the liquidity beta by Pastor and Stambaugh (2003). *Momentum* is the momentum factor created by Carhart (1997). *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et al. (2006). The p-values for the overlapping Fama-Macbeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.

Table 9: **Excluding Financial Firms**

	I	II	III	IV	V	VI
α	0.0502	0.0786	0.0512	0.0544	0.0519	0.0758
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Market	0.0623	0.0566	0.0616	0.0521	0.0556	0.0556
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
SMB		2.23		2.608	2.853	2.294
		(0)***		(0)***	(0)***	(0)***
HML		-2.785		-2.847	-2.8	-2.758
		(0)***		(0)***	(0)***	(0)***
Fortune			-0.0252	-0.0117	-0.0063	0.0064
			(0.002)***	(0.038)**	(0.292)	(0.162)
Disaster			0.0193	0.0194	0.0181	0.0194
			(0.001)***	(0)***	(0)***	(0)***
Momentum		5.689			5.922	5.729
		(0)***			(0)***	(0)***
Liquidity		0.0214			0.0241	0.0216
		(0)***			(0)***	(0)***
Coskewness		0.022				0.0193
		(0.045)**				(0.065)*
Cokurtosis		-1.363				-1.428
		(0)***				(0)***

This table shows the results of Fama-MacBeth (1973) regressions of 60-month excess returns on realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. The assets with sic codes between 6000 and 6200, i.e. financials, are excluded. The number of stocks in each rolling window varies from 1343 to 3311. *Market* is the CAPM beta. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. HML and SMB are high minus low and small minus big factors (Fama and French,1996) respectively. *Liquidity* is the liquidity beta by Pastor and Stambaugh (2003). *Momentum* is the momentum factor created by Carhart (1997). *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et al. (2006). The p-values for the overlapping Fama-Macbeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.

Table 10: **Financial Firms**

	I	II	III	IV	V	VI
α	0.065	0.0662	0.057	0.0568	0.0602	0.0617
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
Market	0.0363	0.0459	0.0343	0.038	0.0407	0.0433
	(0)***	(0)***	(0)***	(0)***	(0)***	(0)***
SMB		1.237		1.285	1.434	1.222
		(0.009)***		(0.004)***	(0.002)***	(0.008)***
HML		-1.355		-1.695	-1.309	-1.366
		(0)***		(0)***	(0)***	(0)***
Fortune			0.0181	0.0152	0.0122	0.0095
			(0.048)**	(0.029)**	(0.08)*	(0.113)
Disaster			0.0451	0.0433	0.0479	0.0462
			(0)***	(0)***	(0)***	(0)***
Momentum		5.856			5.984	5.767
		(0)***			(0)***	(0)***
Liquidity		0.0053			0.0126	0.0069
		(0.481)			(0.09)*	(0.367)
Coskewness		0.0176				0.0099
		(0.276)				(0.522)
Cokurtosis		-0.1129				-0.2117
		(0.587)				(0.275)

This table shows the results of Fama-MacBeth (1973) regressions of 60-month excess returns on realized-risk characteristics. The sample period is from July-1963 to December-2015. An overlapping 60-month rolling window is employed on assets which are listed on the NYSE, AMEX, NASDAQ or NYSE Arca. The only assets with sic codes between 6000 and 6200, i.e. financials, are included. The number of stocks in each rolling window varies from 31 to 566. *Market* is the CAPM beta. *Fortune* and *Disaster* are the Fortune and Disaster risk factors created in this paper. HML and SMB are high minus low and small minus big factors (Fama and French,1996) respectively. *Liquidity* is the liquidity beta by Pastor and Stambaugh (2003). *Momentum* is the momentum factor created by Carhart (1997). *Coskewness* and *Cokurtosis* are the systematic risk factors as measured by Ang et al. (2006). The p-values for the overlapping Fama-Macbeth regression are computed using the Newey-West (1987) autocorrelation and hetroskedastic robust standard errors. *, **, *** are indicators for the significance level at 10%, 5% and 1% of the coefficients, respectively.