Crash risk in the Nordic Stock Market - a cross-sectional analysis

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DISCUSSION PAPER

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Abstract

This paper takes the viewpoint of an investor that can invest in the Nordic countries Norway, Sweden, Denmark and Finland. The four markets are treated as one integrated market. In the analysis we investigate whether there exists a risk premium for investing in stocks exhibiting high crash risk, as measured by their lower tail dependence with the rest of the market portfolio. We indeed find evidence that this is the case, and this evidence is in line with previous research done on American and German stocks markets, as well as theoretical predictions in the literature. However, the results are less clear than was the case for the abovementioned markets. Lower tail dependence is estimated using convex combinations of copulas exhibiting different tail dependence characteristics. The results are robust to different portfolio formations and copula selection criteria.

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1 Introduction

1.1 Idea

This paper is based on the following assumption about investor preferences. Investors dislike crash risk. More specifically, investors are willing to pay more for assets that do not perform poorly in bad times. Another way to look at this is that investors demand a risk premium for holding assets which perform poorly in bad times. This makes intuitive sense. Under standard assumptions we know that investors have higher marginal utility during bad times than during good times. It follows that assets that perform well during bad times are worth more to investors than assets that perform poorly during bad times. A textbook exposition of these assumptions can be found in Cochrane (2001). Motivated by such reasoning, Chabi-Yo, Ruenzi, and Weigert (2018) studied the presence of a risk premium in American stocks with exposure to crash risk. The crash risk measure they used will be formally defined later in this article. Informally, they defined the crash risk of a stock as the conditional probability of a very low return given a very low market return. They indeed found a robust positive association between stock crash risk exposure and stock returns. Additionally, Chabi-Yo, Ruenzi, and Weigert (2018) showed that under fairly general assumptions, such a relationship is predicted by standard asset pricing theoretical frameworks.

Motivated by the above, I want to study Nordic stock markets and whether a crash risk premium exists. I have chosen to look at four broad stock indices from Norway, Sweden, Denmark and Finland. I wish to consider the Nordic stock markets as one entity, i.e., to treat all the Nordic stock markets as one big market, for several reasons. Firstly, looking at for example the Norwegian stock market in isolation, one runs the risk of results not being generalizable due to the composition of the index. This is because the Norwegian stock market is heavily dominated by companies in certain sectors, for example the energy sector. A second reason for considering the Nordic stock market as one entity is statistical, namely the sample size. Thirdly, even though the different markets in the Nordic countries are different, the societies are still quite similar. The third reason is not formally testable, but it shall simply be assumed that there is enough commonality between the abovementioned stock markets that it makes sense to consider them as one entity.

1.2 Related Literature

It has been documented in many papers, for example in Longin and Solnik (2001), that equity correlations increase during market downturns. Not only that, the degree to which they increase is markedly higher than during market upturns. This is echoed by Støve and Tjøstheim (2014), where a different measure of dependence is used. Other notable papers investigating asymmetries in the distribution of financial returns are Silvapulle and Granger (2001), Okimoto (2008), Ang and Chen (2002), Hong, Tu, and Zhou (2007), Chollete, Heinen, and Valdesogo (2009) and Garcia and Tsafack (2011). Either implicitly or explicitly, these studies also document that financial returns are not Gaussian. This implies that (Pearson) correlation is no longer a complete measure of the dependence in financial returns. Embrechts, McNeil, and Straumann (2002) gives an overview of properties and pitfalls of correlation as a measure of dependence.

The documented asymmetries above suggests that diversification benefits are present to a lesser extent during market downturns than otherwise. This has implications for investors that are averse to crash risk. If investors are averse to crashes, a large drop in their wealth implies a disproportionately large drop in utility. As such, it is natural to consider a measure of crash risk that considers market downturns. Chabi-Yo, Ruenzi, and Weigert (2018) provides a theoretical motivation for why such a measure of crash risk, which we will define in more detail later, is priced in a stochastic discount factor framework. Further, they analyze empirically whether exposure to crash risk is associated with higher expected stock returns. They find that stocks with low crash risk serve as a hedge during crises and that stocks with high crash risk have higher average future returns.

Agarwal, Ruenzi, and Weigert (2017) conducts a similar empirical study, where they consider equity oriented hedge fund returns rather than stock returns. They find that crash risk affects the cross-sectional variation in fund returns. Both studies find that exposure to crash risk is associated with higher expected returns. It should be mentioned that, though the two studies partly use the same measure of crash risk, they estimate this measure differently. Karagiannis and Tolikas (2019) find that crash risk helps to explain cross-sectional variation in mutual fund returns. They employ the Hill estimator from Hill (1975) to estimate a measure of tail risk developed by Kelly and Jiang (2014). This is an unconditional measure of crash risk, and as such it differs from the measures used in Chabi-Yo, Ruenzi, and Weigert (2018) and Agarwal, Ruenzi, and Weigert (2017), which measures crash risk conditional on a market crash. Kelly and Jiang (2014) themselves investigate tail risk and asset prices and find that cross-sectionally, stocks with high loadings on past tail risk earn an annual three-factor alpha 5.4 % higher than stocks with low tail risk loadings.

Related work has been done with other risk measures. One of them is downside risk, which separates itself from crash risk by not restricting its attention far out in the tails of the relevant probability distributions. Ang, Chen, and Xing (2006) find that the cross section of stock returns reflects a downside risk premium of approximately 6 % per annum. Stocks that covary strongly with the market during market declines have high average returns. Yan (2011) uses option data to investigate how the expected return of a stock is dependent on what he refers to as jump risk and how jump risk can be measured.

There are several alternative measures of crash risk in the literature. One such measure is conditional correlation, i.e. the correlation between two return series conditioned on one of the return series being below a certain threshold. It is noted in Ang and Chen (2002) that calculating correlations conditional on high or low returns induces a conditioning bias in the correlation estimates. This was also noted earlier by Boyer, Gibson, and Loretan (1997). Furthermore, it is well known that correlation as a measure of dependence is sensitive to large realizations of the random variables in question. Therefore, one might expect that conditional correlation is not a very good empirical measure of dependence in the tails of a probability distribution as the conditioning might leave few observations, some of which might be very large in magnitude.

The structure of this paper is as follows. Section 2 outlines the methodology, section 3 presents the data and some summary statistics, section 4 presents the results, section 5 dicusses robustness checks and finally the conclusion follows in section 6. Section 7 contains the appendix.

2 Methodology

We are concerned with a stock's tendency to crash given a market crash. To investigate this, a suitable crash risk measure must be chosen. It is common in finance to measure the association between random variables of interest, for example stock returns, as their Pearson correlation. Embrechts, McNeil, and Straumann (2002) gives an interesting overview of the properties and pitfalls of the Pearson correlation coefficient. If we were to calculate the correlation between the returns of two financial assets, this would give us an estimate of the strength of the linear relationship between the return distributions. As we are concerned with the relationship between extreme returns, one approach could be to calculate the Pearson correlation coefficient of the returns in the tails of the return distributions. This raises several concerns. Firstly, what is an appropriate threshold for defining the tails of the empirical return distribution. Secondly, the further out in the tails of the return distribution we restrict ourselves, the fewer observations we have to estimate the correlation. One should also note that Boyer, Gibson, and Loretan (1997) show that conditional correlation depends highly nonlinearly on the conditioning level of return.

To illustrate why Pearson correlation is incomplete in our investigation, consider figure 1. It shows simulations of 1000 independent observations made with identical marginal distributions and equal correlations of 0.7, but with a different dependence structure. It is quite evident from the figure that in the rightmost plot there is a greater tendency for large realizations of one variable occurring with large realizations of the other variable, as compared to the leftmost plot. This information is lost when calculating the correlation between the variables.

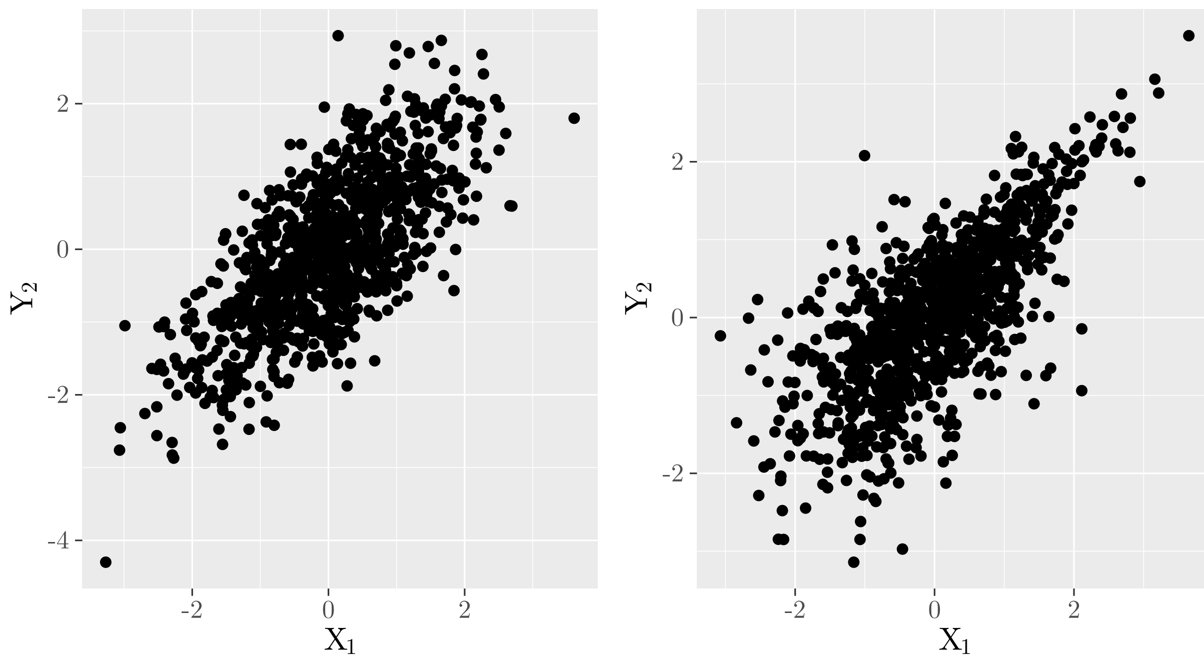
Figure 1 was generated using the concept of a copula function, which will now be introduced. A nice exposition of copula theory can be found in Nelsen (2007). Very briefly put, a copula is a function that "couples" together marginal distribution functions and yields a multivariate distribution function. The usefulness of copulas in finance is due to a theorem which is attributed to Sklar (1959). Consider equation (1)

$$H(x) = C(F_1(x_1), ..., F_d(x_d)), \ x \in \mathbb{R}^d. \tag{1}$$

This equation sums up the parts of Sklar's theorem that are most useful for the purposes of this paper. Briefly, the theorem states that every d-dimensional multivariate distribution function

Figure 1:
Scatter plots

Scatter plot of $n = 1000$ independent observations made with identical marginal distributions and equal correlations of 0.7, but different dependence structure



H has a d-dimensional copula representation C. It also states that we may apply any copula C to d univariate distributions $F_1, ..., F_d$ and the result will be a multivariate distribution function H.

To define our measure of crash risk, consider the pair of random variables (X_1, X_2), in our case representing bivariate returns, with corresponding cumulative distribution functions (F_{X_1}, F_{X_2}). Let X_1 represent the return of a stock and X_2 the return of the market portfolio. To investigate left tail dependence, we could ask about the probability of a low stock return, given a low market return. Formally, this can be represented as

$$L(q) = \Pr\left[X_1 < F_{X_1}^{-1}(q) | X_2 < F_{X_2}^{-1}(q)\right], \tag{2}$$

where q is some quantile. We could then ask ourselves about the dependence far out in the left tail, formally defined as

$$\text{LTD} := \lim_{q \to 0^+} L(q), \tag{3}$$

where LTD stands for lower tail dependence. Upper tail dependence (UTD) is defined analogously as

$$\text{UTD} := \lim_{q \to 1^-} U(q), \tag{4}$$

where we have

$$U(q) = \Pr\left[X_1 > F_{X_1}^{-1}(q) | X_2 > F_{X_2}^{-1}(q)\right]. \tag{5}$$

LTD and UTD can be calculated as properties of the copula associated with the bivariate distribution of (X_1, X_2) by the formulas

$$\text{LTD} = \lim_{q \to 0^+} \frac{C(q,q)}{q} \text{ and } \text{UTD} = \lim_{q \to 1^-} \frac{1 - 2q + C(q,q)}{1-q}. \tag{6}$$

To estimate LTD and UTD then, we will estimate the copulas that determine the dependence between individual stock returns and market returns. The estimation of these copulas will be outlined in the next section.

2.1 Estimating the crash risk measure

We follow Chabi-Yo, Ruenzi, and Weigert (2018) and calculate a market return for each individual stock to avoid endogeneity problems. Specifically, we calculate the value-weighted market return for stock i by excluding stock i from the market portfolio. This is particularly important when we are looking at stock data from indices which are dominated by a few big stocks.

One implication of Sklar's theorem is that we may estimate the marginal distributions of individual stock returns and market returns separately from their dependence structure. Accordingly, we must choose whether to estimate the marginal distributions parametrically or non-parametrically, and similarly for the copulas. Following Chabi-Yo, Ruenzi, and Weigert (2018), marginal distributions are estimated non-parametrically by their scaled distribution functions, while the copulas are estimated parametrically. The choice to estimate the marginal distributions non-parametrically is made to avoid misspecification. For the copulas, however, it will be convenient to perform parametric estimations so that we may calculate LTD and UTD according to (6). To mitigate the misspecification concern when estimating the copulas, several copulas are estimated and the most appropriate one is chosen according to a decision criterion that will be outlined later.

Many copulas that are convenient to work with do not allow for modeling LTD and UTD simultaneously. Typically, they exhibit only one of either LTD, UTD or NTD (no tail dependence). It is easy to show that every convex combination of copula functions is again a copula, see for example Tawn (1988). This allows us to consider copulas with more complicated tail dependence properties by using convex combinations of copulas exhibiting either LTD, NTD or UTD. Table 1 sums up the different copulas used in this study.

Table 1: Copulas from each category

LTD	NTD	UTD
Clayton	Gauss	Gumbel
Rotated Gumbel	Frank	Joe
Rotated Joe	FGM	Galambos
Rotated Galambos	Plackett	Rotated Clayton

All possible combinations consisting of one copula from each category is considered, i.e. 64 in total. Formally, such a combination is represented as

$$C(u_1, u_2; \Theta) = w_1 \cdot C_{\text{LTD}}(u_1, u_2; \theta_1) + w_2 \cdot C_{\text{NTD}}(u_1, u_2; \theta_2) + (1 - w_1 - w_2) \cdot C_{\text{UTD}}(u_1, u_2; \theta_3), \quad (7)$$

where Θ denotes the copula parameters to be estimated, which are θ_i for $i = 1, 2, 3$ for the three copulas in each of the 64 combinations and w_i for $i = 1, 2$ are non-negative weights that sum to $1 - w_1 - w_2 \geq 0$, such that all weights in the convex combination are non-negative and sum to 1. Details of the estimation procedure will be outlined below. Common for estimation of the marginal distributions of stock returns r_i and market returns r_m, as well as estimation of the copula parameters, is a rolling estimation window with a length of 12 months and a rolling interval of 1 month. As previously mentioned, we require at least 100 observations per year, which implies that the number of observations used in each estimate will range between 100 and about 250.

The length of the estimation window reflects a trade off between the number of observations needed for precise estimates and a desire to capture time-varying dependence in the bivariate distribution of r_i and r_m.

Consider a random sample of size n from the bivariate distribution $F(r_i, r_m) = C(F_i(r_i), F_m(r_m))$ of an individual stock return r_i and the market return r_m. F_i and F_m are the corresponding marginal distributions and C is some copula. To be clear, n denotes the number of daily return observations. F_i and F_m are estimated as

$$\hat{F}_i(x) = \frac{1}{n+1} \sum_{k=1}^{n} \mathbb{1}_{r_{i,k} \leq x} \text{ and } \hat{F}_m(x) = \frac{1}{n+1} \sum_{k=1}^{n} \mathbb{1}_{r_{m,k} \leq x}, \quad (8)$$

where $\mathbb{1}_{p(y)}$ is the indicator function which is equal to 1 whenever the proposition $p(y)$ is true and 0 otherwise. F_i and F_m are rescaled empirical distribution functions. We scale by $n+1$ instead of n because some of the copula densities are not well behaved at the borders of their support. Next, one has to estimate the copula parameters Θ_j for each combination $j = 1, ..., 64$. This is done by a maximum likelihood procedure from Genest, Ghoudi, and Rivest (1995). Formally, the estimate $\hat{\Theta}_j$ is given by

$$\hat{\Theta}_j = \text{argmax}_{\Theta_j} L_j(\Theta_j) \text{ with } L_j(\Theta_j) = \sum_{k=1}^{n} \log(c_j(\hat{F}_{i,r_{i,k}}, \hat{F}_{m,r_{m,k}}; \Theta_j)), \tag{9}$$

where $c_j(.,.;\Theta_j)$ is the copula density corresponding to combination j so that $L_j(\Theta_j)$ is the log-likelihood function corresponding to combination j.

2.2 Copula selection criterion

To my knowledge, in the literature there does not exist a widely agreed upon criterion for selecting the most appropriate copula. We follow Chabi-Yo, Ruenzi, and Weigert (2018) and calculate a measure of the distance between each copula and the empirical copula function. To define the empirical copula function, let $(R_{i,k})_{k=1}^n$ denote the rank statistic of the sample $(r_{i,k})_{k=1}^n$ of individual fund return observations from fund i, and similarly let $(R_{m,k})_{k=1}^n$ denote the rank statistic of a corresponding sample of market returns. Now consider the lattice

$$L = \left[\left(\frac{t_i}{n}, \frac{t_m}{n} \right), t_i = 0, 1, ..., n, t_m = 0, 1, ..., n \right].$$

The empirical copula function is defined on L by the following equation:

$$\hat{C}_{(n)} \left(\frac{t_i}{n}, \frac{t_m}{n} \right) = \frac{1}{n} \sum_{k=1}^{n} \mathbb{1}_{R_{i,k} \leq t_i} \cdot \mathbb{1}_{R_{m,k} \leq t_m}. \tag{10}$$

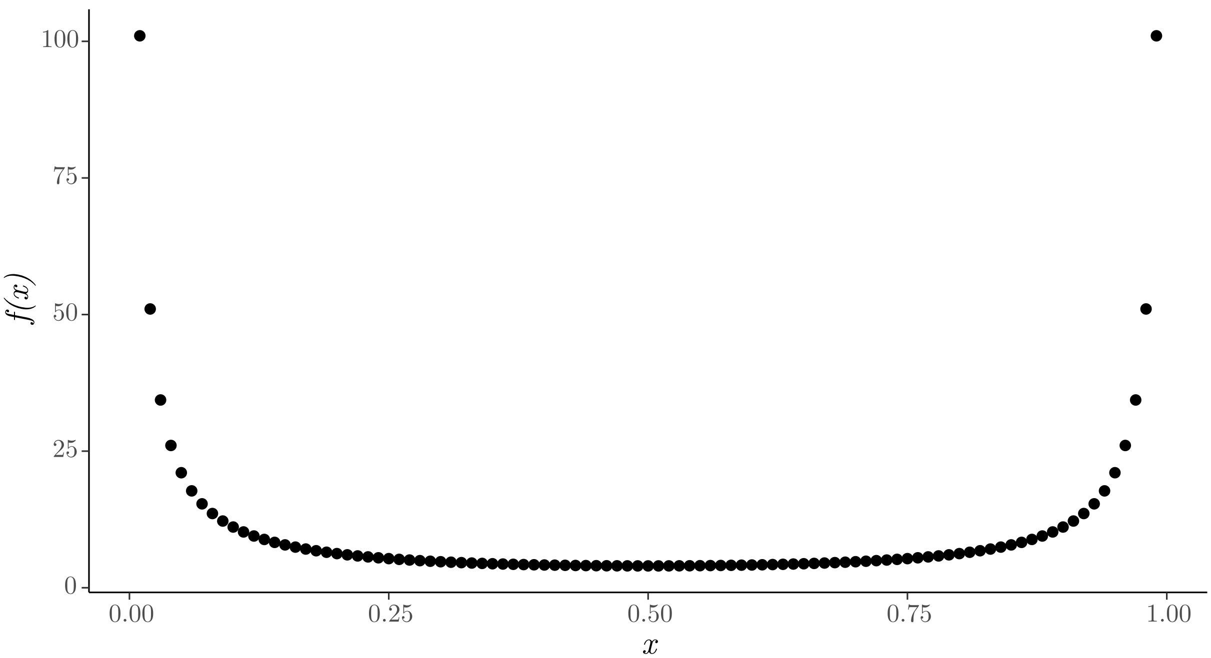
The Integrated Arlington Distance is chosen as a measure of distance between the estimated copulas $C_j(.,.;\Theta_j)$ and the empirical copula $\hat{C}_{(n)}$. It is calculated as

$$D_j = \sum_{t_i=1}^{n} \sum_{t_m=1}^{n} \frac{\left(\hat{C}_{(n)} \left(\frac{t_i}{n}, \frac{t_m}{n} \right) - C_j \left(\frac{t_i}{n}, \frac{t_m}{n}; \hat{\Theta}_j \right) \right)^2}{C_j \left(\frac{t_i}{n}, \frac{t_m}{n}; \hat{\Theta}_j \right) \cdot \left(1 - C_j \left(\frac{t_i}{n}, \frac{t_m}{n}; \hat{\Theta}_j \right) \right)}. \tag{11}$$

One can thus interpret the Integrated Arlington Distance (IAD) as a measure of the distance between the predicted value of the parametric copulas $C_j(.,.;\hat{\Theta}_j)$ and the empirical copula $\hat{C}_{(n)}$ for every point in L. By looking at figure 2 it is clear that IAD puts substantially more weight on observations in the tails of the distribution. Hence, IAD measures the weighted squared difference from the predicted value of the parametric copulas $C_j(.,.;\hat{\Theta}_j)$ to the empirical copula $\hat{C}_{(n)}$ for every point in L, with far greater weights put on points in the tails. Whichever copula $C_j(.,.;\hat{\Theta}_j)$ for $j = 1, ..., 64$ that minimizes D_j will be considered the best fit to the data, and will therefore be used to calculated LTD and UTD.

Figure 2:
Illustration of weighting in IAD

Plot of the function $f(x) = \frac{1}{x(1-x)}$ for $0 < x < 1$.



2.3 Alternative copula methodology

A notable contribution to the part of the finance literature concerned with copula applications is Patton (2006). It introduces the notion of a conditional copula and applies it to the modeling of asymmetric exchange rate dependence. Furthermore, the approach taken to copula selection is quite different. Patton (2006) chooses a copula and models time variation in the copula parameter. This can be called a dynamic copula approach, in contrast to the static copula approach taken in Chabi-Yo, Ruenzi, and Weigert (2018), where the copula can change per time period. Supper, Irresberger, and Weiß (2020) performs a simulation study where they compare different tail dependence estimators. Amongst these estimators are the one used in

Patton (2006) and the one used in Chabi-Yo, Ruenzi, and Weigert (2018). They find that the dynamic copula approach of Patton (2006) has superior performance to Chabi-Yo, Ruenzi, and Weigert (2018) in their simulation study. One could note that their data generating process is similar to the process given by a dynamical copula.

2.4 Some comments on the methodology

There are at least two ways to estimate a parameter of interest that is tied to a statistical distribution. One can either try to estimate the parameter directly, or one can try to estimate the associated distribution and infer the parameter. This paper follows the latter approach. Modeling the distribution as opposed to the parameters in our case has the advantage of being able to make use of all the available information in the empirical return distribution. Further, and contrasting with the approach taken by Patton (2006), the approach of this paper demands fewer assumptions about the copula family behind the data generating process. Lastly, the aim of the procedure is to capture some dynamics of the dependence structures in the data by updating the best fitting copula every time period. However, it is not clear that the procedure possesses this latter property. Intuitively, we are optimizing over a multidimensional surface that may be rugged. As we rely on optimization algorithms, there is no way of guaranteeing that we are not getting stuck in some local optimum that is not the optimum copula specification. One may also imagine that this can cause estimates for certain time periods to be quite imprecise, in the sense that the estimated LTD varies quite a lot from, say, week to week.

2.5 Concerns about the methodology

No formal test has been done to investigate the extent to which the mixed densities applied in this study may be rugged in nature. A potential way to mitigate this concern is to employ some sort of stochastic optimization algorithm. This has not been done in this study. Another concern that has been mentioned earlier is the sample size used for estimating individual stock LTD. One year of observations equates to roughly 250 observations, with some stocks having as few as 100 valid return observations per year. Optimally, we would like to have many more observations to be more confident that the numerical LTD estimates converge to the true value. The choice of estimation window is a trade-off between sample size and a changing nature of dependency between variables. It is difficult to argue that LTD should not change given changes in market conditions, and market conditions do change over time. Hence, having an estimation window of, say, 10 years, one would have to argue that individual stock LTD remains largely unchanged over a 10 year period. This trade-off is also the reason why we are estimating LTD based on daily returns, and analyzing the average effect of LTD on monthly returns. Estimating LTD on monthly returns results in too few observations. Also, it seems reasonable that LTD should not change much from day to day, so we make the assumption that estimated LTD remains constant for the following month.

3 Data

3.1 The sample

We consider four stock markets in the Nordic countries, namely the Norwegian, Swedish, Danish and Finnish stock markets. The period under question is the beginning of 1999 to the end of 2022. For each market, we download all listed shares, both currently listed and delisted. The relevant lists from Thomson Reuters Datastream are LOSLOASH, LSWEALI, LCOSEASH and LHEXINDX, which contain all the currently listed shares in the respective countries, and DEADNW, DEADSD, DEADDK and DEADFN, which contain all the delisted shares in the respective markets. The relevant share variables are the total return index (RI), the price (P) and the market value (MV). As a proxy for the risk-free rate, we use the EURIBOR 1 month rate. More specifically, we downloaded the total return index (RI) of the variable EIBOR from Thomson Reuters datastream, and calculated the returns as in (12). All the relevant share variables are converted to euro using exchange rates downloaded from the ECB[1].

Compared to, say, American stock data, there are considerably fewer stocks in the chosen indices. To make meaningful statistical estimations and inferences, we therefore consider the four markets as one entity - the Nordic stock market. We exclude all observations that are missing either closing price, closing return or number of shares issued. Further, we require at least 100 valid return observations per year.

Several stocks have different stock classes, namely A, B and C stocks. For the purposes of investigating the effect of crash risk on stock returns, one could argue that this difference could matter for example in the event of a bankruptcy. However, the different stock classes are still stocks written on the same company, and hence they should represent the same fundamental company characteristics. Keeping several classes of stocks for the same company could influence results when investigating the average association between crash risk and stock returns. Anecdotally, the sample contains noticeable return differences between certain A and B stocks written on the same company. To investigate further, we sorted the sample on company names and investigated what was identified as different classes of stock written on the same company. No stocks were removed from the sample on this basis.

Some care must be taken when using Datastream's total return index to calculate daily returns for each stock. Likely due to rounding errors, some total return index observations was listed as 0. This is obviously wrong. However, this has consequences when we calculate returns as

$$r_t = \frac{TI_t}{TI_{t-1}} - 1, \tag{12}$$

[1]https://sdw.ecb.europa.eu/browse.do?node=9691296, downloaded February 1 2023.

where TI_i is the value of the total return index at time t, i.e. we get a division by zero, which corresponds to infinite returns. Any such observations were removed from the sample. It should be noted that such observations were few. However, this problem also highlights that for low values of the total return index, there might be some imprecise return estimates, or one might have unstable returns for some stocks over a certain time period. If we investigate the returns, we see that on a daily level we have stock returns ranging from almost -1 to 262. Some of these are likely not correct, and can be attributed to rounding error, as just described. If we aggregate returns to monthly levels, we get returns ranging from -1 to 10377166, which seems very unrealistic. Therefore, the problem must be addressed. There exists no objective criterion for determining what is a true extreme return outcome and what can be attributed to data errors. We elected to remove (slightly more than) the smallest 1 percent of the stocks in the sample. More specifically, we did the following. For every date, we identified the 1 percent smallest stocks in the sample as measured by their market value. If a stock at one point in time was one of the smallest stocks, we removed it from the sample entirely. The reason for not only removing the stock from the part of the sample where it was one of the smallest is the following. Firstly, doing this one could be left with return observations that are widely spaced on time, so that we no longer can consider them daily, or maybe even monthly returns, but returns over other unspecified time periods. Such gaps in the data are not desirable when conducting the data analysis. Secondly, several small stocks seem to have very unstable return distributions, to the point where the distributions seem likely to arise from measurement errors.

3.2 Comments on the data

The analysis takes the viewpoint of an investor that can invest in all the Nordic markets under study. For that reason, and in order to be consistent when performing the analysis, we have chosen to convert all relevant variables, so that returns are euro denominated, and relative market weights are calculated using EUROs. This choice has implications for the estimations of the lower tail dependence coefficients (LTD), the details of which are described in Section 2. Stocks in the Scandinavian countries are traded in the local currencies. Returns are now affected both by investor behavior and by exchange rate movements. To make this clear, consider a stock where there is no trading during the course of two days, but for which we have a total return index observation. The price of this stock will remain constant in the local currency, say the Norwegian krone (NOK), as will the total return index. However, if there is a change in the NOK-EURO exchange rate, there will be a nonzero change in the euro denominated total return index.

The time period coincides with the introduction of the euro. This is intentional and is done in order to be consistent with what we consider to be the most relevant risk-free rate, namely the EURIBOR 1 month rate. Thomson Reuters datastream provides an artifical euro exchange rate before 1999, so in theory it would be possible to extend the window of analysis further in the past. We do not want to introduce potential errors by such an artifical exchange rate.

One could alternatively convert all relevant variables to another currency that has existed for the whole period, and download a corresponding relevant risk-free rate.

A note is in order for how we justify using daily returns for estimating LTD when the rest of the analysis is carried out on a monthly time scale. When Chabi-Yo, Ruenzi, and Weigert (2018) calculates LTD and UTD, they use rolling windows of 12 months of daily data with a frequency of 1 month. They then look at the association between monthly average returns and LTD, where the LTD is derived from the copula estimated on daily data. It has been documented in the literature, for example in Botta et al. (2015), that the distribution of stock returns changes depending on the time scale. This makes sense intuitively if we consider log returns and the central limit theorem, as we may consider monthly log returns as the sum of daily log returns. One might expect some central limit theorem effect to take place when we go from daily returns to monthly returns, at least if the underlying return distributions of daily stock returns are sufficiently well behaved. There is of course an obvious trade off here. If we were to estimate LTD based on monthly data, we would need a substantial time window of observations to be able to hope for precise estimates of LTD. This would require us to assume that the dependency between the returns of individual stocks and returns of the market remains unchanged over large time periods. Such an assumption is hard to justify. There are, however, several ways of motivating the approach taken in Chabi-Yo, Ruenzi, and Weigert (2018). Firstly, if one is interested in the association between average returns and LTD on the same time scale, one could argue that there is little reason to assume that LTD is very different on monthly time scales than on daily time scales. A non rigorous theoretical justification for this is the well known result that the distribution that arises from aggregation of returns, due to the central limit theorem, converges very fast in the central part of the distribution, but much slower in the tails. Another justification is also due to the aggregation of daily returns to monthly returns. Large absolute monthly returns may be the chance of many consecutive days of smaller returns with the same sign, or the may be driven by some large daily returns. An extreme example illustrates this point. If you have one day of -50% return followed (or preceded) by 24 consecutive days of 1% returns, you end up with 63.5% of your initial wealth, while if you have 25 days of consecutive -1% returns you end up with 77.8% of your initial wealth. This means that if there is a risk premium associated with stocks having high LTD with the market, the risk premium should be at least partially reflected in the LTD with the market calculated on daily returns.

3.3 Summary statistics

Figure 3 shows the number of stocks in any given month in the sample. We now turn to summary statistics for LTD across the whole panel of data, i.e. across all stocks and all dates in our dataset.

We can see in table 2 that there is considerable variation in LTD across the sample, from 0 all the way to 0.81. One quarter of all observations have an estimated LTD coefficient of about 0. The median LTD coefficient is 0.115, and three quarters of all observations have an estimated

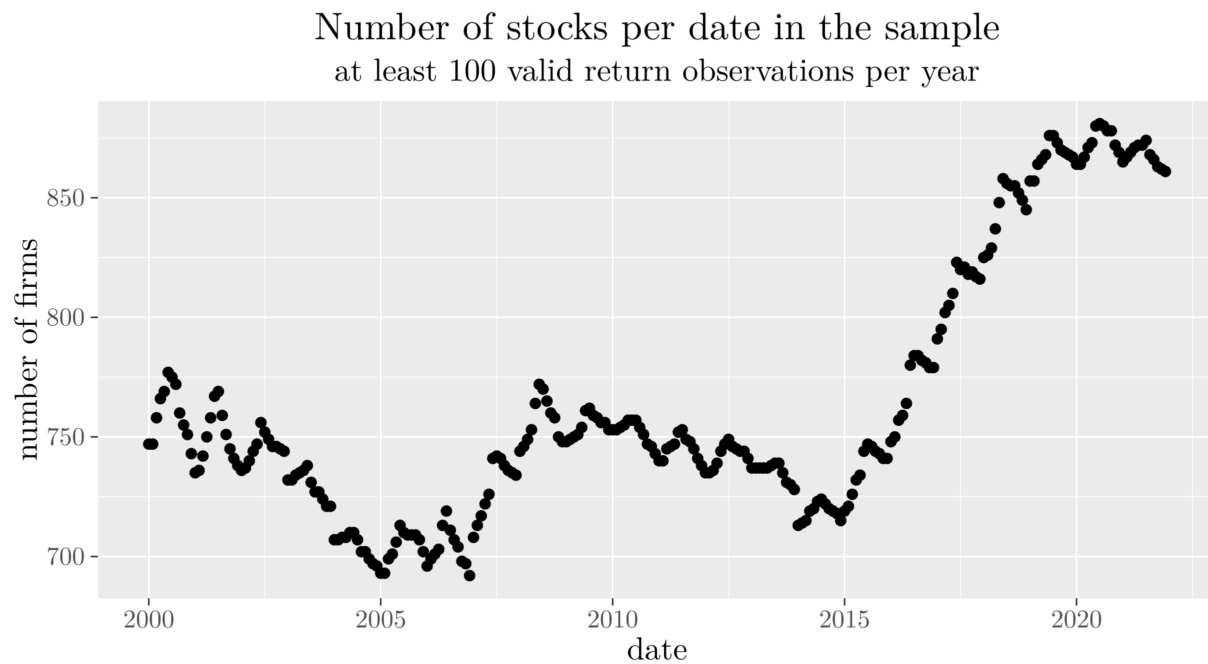


Figure 3: This plot shows the number of firm observations per month in the Nordic market. Each stock in the sample is required to have at least 100 return observations per year.

LTD less than 0.235. The average LTD is higher than the median LTD, though the difference is not big.

Table 3 displays summary statistics for return based variables (except LTD and UTD). We may note that the average downside beta is higher than the average upside beta, but also with a noticeably higher interquartile range. This can be interpreted in line with the evidence in the literature that correlations tend to increase in market downturns more so than in upturns, though we have not formally tested for a statistical difference between the two quantities. Average and median monthly stock returns are positive and close to zero, and as should be expected the interquartile range is larger for individual stock returns than for the monthly index returns (recall that the monthly index returns are individual for each stock, and is calculated as the value-weighted market return from all other stocks in the sample). The average cokurtosis is positive, but indistinguishable from zero with two decimals of precision. A positive average cokurtosis would indicate that extreme returns tend to occur somewhat simultaneously. The average coskewness is negative, which suggests that stocks tend to have high negative returns simultaneously as the market exhibits high negative returns

Table 4 displays the correlation matrix of all the return based variables in this study. The

Table 2:
LTD summary

This table summarises the distribution of LTD estimates across the pooled sample, i.e. across all stocks and dates.

Minimum	**1st Quartile**	**Median**	**Mean**	**3rd Quartile**	**Maximum**
0	0.033	0.144	0.166	0.263	0.811

Table 3:
Summary Return Based Variables

Summary statistics for return based variables (except LTD and UTD). It should be read as: mean/median (IQR), where IQR stands for interquartile range.

Characteristic	**n = 186,086**
Beta	0.38 / 0.18 (0.67)
Coskewness	-0.09 / -0.07 (0.39)
Cokurtosis	0.00 / 0.00 (0.01)
Downside beta	0.69 / 0.65 (0.93)
Upside beta	0.27 / 0.03 (0.44)
Monthly stock return	0.01 / 0.00 (0.08)
Monthly index return	0.001 / 0.000 (0.008)

variable that exhibits the highest correlation with LTD is downside beta, while the variable that exhibits the highest correlation with UTD is upside beta. We may also notice that the correlation between LTD and UTD is low. An interpretation is that stocks exhibiting a tendency of crashing when the market crashes do not necessarily exhibit the same tendency of booming when the market booms. This can be seen as a partial justification for the choice of flexible combinations of copulas for modeling the dependence structure between individual stocks and the market. Further, LTD exhibits low correlation with both cokurtosis and coskewness. If one were only to interpret the signs of the correlation coefficients between LTD and the two variables cokurtosis and coskewness, then the correlations are in line with what was observed in the previous paragraph. To be more specific, an increase in cokurtosis indicates that extreme returns to an increasing degree occurs simultaneously. Hence, if LTD and cokurtosis both captures such a characteristic of stock returns, one would expect the correlation between the two to be positive. The interpretation is similar for coskewness, where one would expect a negative correlation coefficient. However, one should not interpret only the signs of the correlation coefficients, as the size of the coefficients are very small. Squaring the values, one could interpret the different correlations as the R-squared in a univariate regression of LTD on the respective variables. It then becomes clear that in a pooled univariate linear regression framework, cokurtosis and coskewness explains next to none of the variation in LTD.

Table 4:
Correlation matrix return based variables

This table displays the correlation matrix for all the return based variables used in this study

	LTD	UTD	β	β^+	β^-	Coskewness	Cokurtosis
LTD	1						
UTD	0.193	1					
β	0.397	0.267	1				
β^+	0.263	0.308	0.854	1			
β^-	0.577	0.183	0.656	0.475	1		
Coskewness	-0.117	0.067	-0.042	0.046	0.008	1	
Cokurtosis	0.019	-0.006	0.004	0.003	0.033	0.528	1

4 Results

4.1 Univariate sorts

Table 5:
Future returns sorted on LTD

Stocks have been sorted into quintiles based on their estimated LTD. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied LTD values, the first observation with that LTD value is ranked lower than the following observation with the same LTD value. This pattern repeats in the presence of more than two ties.

Quintile	Returns	P-value
1 Weak LTD	0.389%	0.316
2	0.511%	0.113
3	0.62%**	0.023
4	0.731%**	0.017
5 Strong LTD	0.579%	0.169
Strong - Weak	0.191%	0.482

We start by considering univariate portfolio sorts where we sort on LTD. We sort the data into quintiles based on their estimated LTD coefficient in month t and wish to investigate the corresponding return distribution of the LTD sorted portfolios. Within each quintile, we calculate the value-weighted portfolio return for month $t+1$ using weights calculated at time t. This gives five time series of LTD sorted portfolio returns. Averaging over these time series, we get an estimate of expected returns within each quintile. We also calculate the expected one-month-ahead return of a long-short portfolio of stocks that exhibit strong LTD (the upper quintile) and stocks that exhibit weak LTD (the lower quintile). The results are reported in table 5.

The univariate results are much in line with what was found in Chabi-Yo, Ruenzi, and Weigert (2018), though of much smaller economical significance. There is an almost uniform increase in average portfolio returns as we move from the quintile with the lowest LTD estimates to the quintile with the highest LTD estimates. The pattern is broken only at the highest LTD quintile, where the average one-month-ahead returns are lower than in the prior quintile, but still positive and higher than in the first two quintiles. The long-short portfolio sorted on LTD thus exhibits positive average one-month-ahead returns. The long-short portfolio returns are not economically significant, and only the portfolio returns of quintile 3 and 4 exhibit one-month-ahead returns that are statistically distinguishable from zero at the five percent significance level. To illustrate the economic significance, note that the standard deviation of the one-month-ahead returns of the long-short portfolio is 0.0028. A one standard deviation increase in the returns of the long-short portfolio translates into a $0.0028 \times 0.191\% \times 12 = 0.006\%$ increase in the annualized excess return of the long-short portfolio. One can interpret the univariate results as support for the hypothesis that the risk premium to investing in stocks that are exposed to higher levels of crash risk is small. If we interpret it to be positive this is in line with the theoretical results in Chabi-Yo, Ruenzi, and Weigert (2018), but the theoretical predictions are not clearly verified by the univariate sorting on LTD. The results are not inconsistent with the corresponding empirical results in Supper, Irresberger, and Weiß (2020). That such a risk premium should exist makes intuitive sense if we consider expected utility theory. The marginal utility of an investor is higher in bad times, and hence the investor requires a risk premium for investing in stocks with higher probability of poor returns when the market performs particularly poorly.

Next we consider table 6, which displays one-month-ahead value weighted portfolio returns of stocks sorted into quintiles based on their estimated UTD value in the prior month. We almost observe the opposite pattern than when we sorted on LTD. One-month-ahead returns are generally decreasing as a function of UTD quintile, with the exception of moving from quintile 3 to quintile 4. The long-short portfolio exhibits a negative one-month-ahead average return. The estimated average one-month-ahead portfolio returns are not all statistically distinguishable from zero at the five percent significance level. We may note, however, that the negative long-short portfolio return is indeed statistically significant at the five percent level. Hence, there seems to be a negative risk premium associated with investing in stocks that do particularly well when the market performs particularly well. A one standard deviation increase in the annualized excess return of the long-short portfolio translates into a $0.0024 \times 0.691\% \times 12 = 0.02\%$ decrease in the annualized excess return of the long-short portfolio, which is not a large decrease.

We also check whether the positive return spread on LTD sorted portfolios, albeit not statistically significant or big in economic terms, can be explained by the Fama and French

(1993) factor model. We do so by performing a regression of the return spread on the factors. Note that the explanatory variable here is not the same as in section 4.3, where we regress one-month-ahead returns on different stock characteristics. The results are displayed in table 7. The factor model accounts for little of the variation in the monthly return spread. For each specification there is an associated positive alpha. However, it is not statistically significant. This is perhaps not surprising considering that the mean return spread in table 5 was statistically distinguishable from zero.

Before moving on the double sorts, we issue a word of caution. The above analysis of univariate sorts rests on the assumption that the different quintile portfolios represent well diversified investments that differ only in the level of the sorting variable, i.e. the level of LTD/UTD. There are fewer stocks in each quintile in the Nordic market analysed in this study compared to the American stock market. Hence, this assumption may be less well founded in this analysis than in the analysis conducted in Chabi-Yo, Ruenzi, and Weigert (2018).

Table 6:
Future returns sorted on UTD

Stocks have been sorted into quintiles based on their estimated UTD. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied UTD values, the first observation with that LTD value is ranked lower than the following observation with the same UTD value. This pattern repeats in the presence of more than two ties.

Quintile	Returns	P-value
1 Weak UTD	1.071%***	0.001
2	0.805%***	0.010
3	0.254%	0.413
4	0.626%*	0.051
5 Strong UTD	0.454%	0.276
Strong - Weak	-0.617%**	0.019

Table 7:
Trading strategy

Regression of one-month-ahead value-weigthed long short portfolio returns (strong LTD stocks minus weak LTD stocks) on the factors from the Fama and French (1993) three-factor model . (1) is a univariate regression on the market return in excess of the risk-free rate, (2) adds the HML factor, and (3) adds the SMB factor. The construction of the HML and SMB factors are outlined in the Appendix in section 7.2.

Dependent Variable:	$LTD5_{r_{t+1}} - LTD1_{r_{t+1}}$		
Model:	(1)	(2)	(3)
Variables			
(Intercept)	0.0026	0.0033	0.0043
	(0.0029)	(0.0028)	(0.0030)
$r_m - r_f$	-0.0576	-0.1042*	-0.1150*
	(0.0584)	(0.0580)	(0.0592)
HML		-0.2460***	-0.2369***
		(0.0622)	(0.0629)
SMB			-0.0615
			(0.0664)
Fit statistics			
Observations	261	261	261
R^2	0.00375	0.06075	0.06388
Adjusted R^2	-9.8×10^{-5}	0.05347	0.05295

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.2 Double sorts

In this section we first create portfolios of stocks based on quintiles of some return based variable other than LTD, and then we repeat the univariate analysis above within each such quintile. The return based variables under consideration are beta, downside beta from Ang, Chen, and Xing (2006), coskewness, which was shown to be negatively associated with higher expected returns in Harvey and Siddique (2000), and cokurtosis, which was shown to be positively associated with higher expected returns both in Fang and Lai (1997) and Dittmar (2002).

Table 8:
Future returns sorted on beta and LTD

Stocks have been sorted into quintiles based on their estimated beta and LTD. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied beta and/or LTD values, the first observation with that beta/LTD value is ranked lower than the following observation with the same beta/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low β	2	3	4	5 High β
1 Weak LTD	0.524%*	0.942%***	0.622%	1.038%**	0.519%
2	0.683%***	0.523%**	1.051%***	0.562%	0.767%
3	0.492%**	0.493%**	0.866%***	0.588%	0.507%
4	0.494%*	0.824%***	1.057%***	1.082%***	0.235%
5 Strong LTD	0.71%***	0.697%**	1.194%***	0.766%**	0.786%
Strong - Weak	0.185%	-0.245%	0.572%*	-0.272%	0.268%

Table 8 displays one-month-ahead average future returns for value weighted portfolios that have been double sorted on beta and LTD. We note that the long-short portfolios do not exhibit a clear pattern in the average one-month-ahead returns. There is also no clear discernible pattern across the LTD quintiles within the different beta quintiles. Had LTD been completely independent of beta one would expect to see results similar to what we saw when we sorted only on LTD.

Table 9 displays one-month-ahead average future returns for value weighted portfolios that have been double sorted on cokurtosis and LTD. All long-short portfolios now exhibit positive average one-month-ahead returns, though none are statistically indistinguishable from zero. The increases in average future returns are not monotonic, though there appears to be a generally increasing pattern as we move from portfolios of stocks that exhibit weak LTD to portfolios of stocks that exhibit strong LTD. These results seem to be in line with what has been documented for the American and German stock markets in Chabi-Yo, Ruenzi, and Weigert (2018) and Supper, Irresberger, and Weiß (2020), respectively.

Table 10 displays one-month-ahead average future returns for value weighted portfolios that have been double sorted on coskewness and LTD. All long-short portfolios, with the exception of the one consisting of high coskewness sorted stocks, exhibit positive average one-month-ahead returns. There are no monotonic increases in average future returns, and it is less clear than was the case for cokurtosis sorted stock portfolios that there is a general increase in average future returns as we move from portfolios of stocks exhibiting weak LTD to portfolios of stocks exhibiting strong LTD.

Lastly we consider Table 11, which displays one-month-ahead average future returns for value weighted portfolios that have been double sorted on downside beta and LTD. The same remarks that were given for coskewness sorted stock portfolios apply here, but with a different long-short portfolio exhibiting negative one-month-ahead returns.

Table 9:
Future returns sorted on cokurtosis and LTD

Stocks have been sorted into quintiles based on their estimated cokurtosis and LTD. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied cokurtosis and/or LTD values, the first observation with that cokurtosis/LTD value is ranked lower than the following observation with the same cokurtosis/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low Cokurtosis	2	3	4	5 High Cokurtosis
1 Weak LTD	0.385%	0.772%**	0.576%	0.326%	0.256%
2	0.502%	1.001%***	0.88%**	0.389%	0.811%*
3	0.527%**	0.78%***	0.791%***	0.501%	0.373%
4	0.284%	1.465%***	1.069%***	0.796%**	0.485%
5 Strong LTD	0.772%**	1.204%***	0.981%***	0.501%	0.669%
Strong - Weak	0.387%	0.432%	0.405%	0.175%	0.413%

Table 10:
Future returns sorted on coskewness and LTD

Stocks have been sorted into quintiles based on their estimated coskewness and LTD. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied coskewness and/or LTD values, the first observation with that coskewness/LTD value is ranked lower than the following observation with the same coskewness/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low Coskewness	2	3	4	5 High coskewness
1 Weak LTD	0.782%**	0.905%***	0.8%**	0.34%	0.414%
2	0.527%	0.835%***	0.746%**	0.227%	0.508%
3	0.755%*	0.661%**	1.063%***	0.618%	-0.01%
4	1.128%***	0.865%***	1.079%***	0.355%	0.514%
5 Strong LTD	1.003%***	0.961%**	1.025%**	0.411%	0.333%
Strong - Weak	0.221%	0.055%	0.225%	0.072%	-0.081%

Table 11:
Future returns sorted on downside beta and LTD

Stocks have been sorted into quintiles based on their estimated downside beta and LTD. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied downside beta and/or LTD values, the first observation with that downside beta/LTD value is ranked lower than the following observation with the same downside beta/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low β^-	2	3	4	5 High β^-
1 Weak LTD	0.081%	0.515%	0.927%**	0.82%*	0.666%
2	0.37%	0.221%	1.092%***	0.628%	0.238%
3	0.169%	0.841%***	0.836%***	0.511%	0.278%
4	0.113%	0.44%	1.235%***	1.128%***	0.458%
5 Strong LTD	0.252%	1.125%	1.02%***	0.754%**	0.742%
Strong - Weak	0.17%	0.61%	0.093%	-0.066%	0.076%

4.3 Regression analysis

To investigate the association between one-month-ahead returns and more than two variables, we turn to a different tool of analysis than univariate sorts and double sorts, namely multivariate regressions. We begin estimate regressions using clustered standard errors, clustering on the time variable. The results are displayed in table 12. Firstly, we may note that in all the regression specifications, LTD exhibits both an economically and statistically significant positive coefficient when regressed on one-month-ahead returns. Further, the coefficient estimate appears stable across all regression specifications. The other coefficient estimates in the different regression specifications exhibit neither economic nor statistical significance. To illustrate the economic significance, we consider the LTD coefficient estimate in regression specification (2). A one standard deviation increase in LTD translates into a $0.108 \times 0.0303 \times 1200 = 3.93\%$ increase in the annualized one-month-ahead excess returns. The adjusted R-squared is low, but it would be quite remarkable if these regressors alone explained a large portion of stock returns in the Nordic countries. Hence, this was to be expected.

Looking at table 13 we may investigate the effect of adding coskewness, cokurtosis, size as measured by the logarithm of market capitalization and the book-to-market value, respectively. In specification (1) and (2) the coefficient estimates for LTD are slightly diminished compared to the more sparse regression specifications in table 12, but the estimates are still very similar. The coskewness coefficient estimate is statistically indistinguishable from zero before adding cokurtosis to the regression specification. Adding cokurtosis, both coefficient estimates are statistically significant at the 10 percent level. The signs of the coefficient estimates on coskewness and cokurtosis are consistent with our previous discussion, but the absolute size of the estimates are small. Notice that in regression specification (3) and (4) we have significantly fewer observations. This is due to missing accounting data for companies. This means that regression specifications (3) and (4) are not directly comparable to regression specifications (1) and (2). We still note that in this reduced sample, the LTD coefficients have increased notably in size and are now statistically significant at the 1 percent level. Coskewness and cokurtosis are statistically significant at the five percent level, and both of their magnitudes have increased. Their coefficient signs are still consistent with our previous discussion. Further, we confirm previous findings from the literature (for example Fama and French (1993)), namely that firm size has a negative impact on returns, while the book-to-market ratio has a positive impact on returns. To illustrate the economic significance of the LTD coefficient estimates, we focus on regression specification (4). A one standard deviation increase in LTD translates into a $0.108 \times 0.0384 \times 1200 = 4.98\%$ increase in the annualized one-month-ahead excess returns. It is interesting to note that by including downside beta in the regression specifications, we do not diminish the coefficient estimates on LTD notably. This demonstrates that the different measures do not measure equivalent parts of the dependence structure between stock returns and the market.

Table 12:
Multivariate regression results

Regression of one-month-ahead returns on different sets of control variables. The dependent variable is the one-month-ahead return. (1) is a univariate regression on LTD, (2) is a bivariate regression on LTD and beta, (3) is a multivariate regression on LTD, beta and downside beta, and (4) is a multivariate regression on LTD, beta, downside beta and upside beta. In (5) we omit beta since it is quite highly correlated with upside beta and downside beta. This does not result in any noteworthy change in the estimated coefficient on LTD, upside beta or downside beta . Standard errors are clustered on months.

Dependent Variable:			r_{t+1}		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(Intercept)	0.0044	0.0045*	0.0042**	0.0042**	0.0042**
	(0.0026)	(0.0024)	(0.0021)	(0.0021)	(0.0021)
LTD	0.0294***	0.0303**	0.0284**	0.0283**	0.0282**
	(0.0108)	(0.0124)	(0.0130)	(0.0128)	(0.0129)
β		-0.0007	-0.0014	-0.0011	
		(0.0054)	(0.0066)	(0.0091)	
β^-			0.0012	0.0012	0.0009
			(0.0037)	(0.0037)	(0.0033)
β^+				-0.0003	-0.0011
				(0.0067)	(0.0051)
Fit statistics					
Observations	185,660	185,660	185,660	185,660	185,660
R^2	0.00153	0.00154	0.00156	0.00156	0.00156
Adjusted R^2	0.00153	0.00153	0.00155	0.00154	0.00154

Clustered (date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13:
Future returns regressed on different factors

Regression of one-month-ahead returns on different sets of control variables. The dependent variable is the one-month-ahead return. (1) is a multivariate regression on LTD, beta, downside beta, upside beta and coskewness. For each regression, we add one control variable. In (2) we add cokurtosis. Standard errors are clustered on months. In (3) we add size which is the logarithm of market capitalization, and in (4) we add the book to market ratio.

Dependent Variable:	r_{t+1}			
Model:	(1)	(2)	(3)	(4)
Variables				
(Intercept)	0.0041*	0.0041*	0.0289***	0.0240***
	(0.0021)	(0.0021)	(0.0070)	(0.0066)
LTD	0.0262**	0.0252**	0.0385***	0.0384***
	(0.0121)	(0.0119)	(0.0124)	(0.0124)
β	-0.0026	-0.0031	0.0021	0.0016
	(0.0090)	(0.0090)	(0.0096)	(0.0095)
β^-	0.0018	0.0019	-0.0025	-0.0026
	(0.0036)	(0.0036)	(0.0040)	(0.0040)
β^+	0.0009	0.0014	-0.0026	-0.0025
	(0.0065)	(0.0065)	(0.0071)	(0.0071)
Coskewness	-0.0032	-0.0048*	-0.0075**	-0.0075**
	(0.0020)	(0.0027)	(0.0035)	(0.0035)
Cokurtosis		0.0009*	0.0012**	0.0012**
		(0.0005)	(0.0006)	(0.0006)
size			-0.0015***	-0.0014***
			(0.0005)	(0.0005)
bookmarket				0.0025***
				(0.0007)
Fit statistics				
Observations	185,660	185,660	70,245	70,245
R^2	0.00183	0.00197	0.00415	0.00496
Adjusted R^2	0.00180	0.00194	0.00405	0.00484

Clustered (date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5 Robustness Test and Implications

5.1 Robustness

As we previously have expressed concerns that using the Integrated Arlingtod Distance as a decision criterion for choosing the optimal copula specification may lead to unstable LTD estimates, we now redo the analysis using a different copula selection criterion. A natural criterion to use is to choose the copula specification that has the smallest value for its minimized negative log-likelihood function. We start by considering univariate sorts.

Table 14:
Future returns sorted on LTD

Stocks have been sorted into quintiles based on their estimated LTD, but using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied LTD values, the first observation with that LTD value is ranked lower than the following observation with the same LTD value. This pattern repeats in the presence of more than two ties.

Quintile	Returns	P-value
1 Weak LTD	0.375%	0.315
2	0.18%	0.657
3	0.479%	0.104
4	0.925%***	0.004
5 Strong LTD	0.764%**	0.045
Strong - Weak	0.388%*	0.084

Table 14 displays the average one-month-ahead returns of portfolios formed by sorting stocks into value-weighted portfolios based on estimated LTD quintiles, but using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. The results are similar to previous results. There is not a monotonous increase in returns as we move from portfolios of weak LTD stocks to portfolios of high LTD stocks, but the portfolios in the two highest LTD quintiles exhibit significantly higher returns than the portfolios in the two lowest LTD quintiles. The long-short portfolio of strong-weak LTD stocks exhibit a one-month-ahead return of 0.388%, which is statistically different from zero at the 10% level. This is a stronger result than what was found in table 5.

Table 15:
Future returns sorted on beta and LTD

Stocks have been sorted into quintiles based on their estimated beta and LTD, but using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied beta and/or LTD values, the first observation with that beta/LTD value is ranked lower than the following observation with the same beta/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low β	2	3	4	5 High β
1 Weak LTD	0.684%**	0.863%***	0.226%	0.879%*	0.838%*
2	0.465%**	0.621%**	0.763%*	0.414%	0.016%
3	0.32%	0.528%**	0.829%**	0.901%**	0.691%
4	0.594%***	0.707%**	1.093%***	1.053%***	0.608%
5 Strong LTD	0.74%***	0.765%***	1.345%***	0.777%**	0.672%
Strong - Weak	0.056%	-0.098%	1.118%***	-0.102%	-0.166%

Proceeding with double sorts, table 15 displays the average one-month-ahead returns of portfolios formed by sorts on beta and LTD quintiles, again using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. As in table 8 we note that the long-short portfolios do not exhibit a clear pattern in the average one-month-ahead returns. There is also no clear discernible pattern across the LTD quintiles within the different beta quintiles. Had LTD been completely independent of beta one would expect to see results similar to what we saw when we sorted only on LTD. The results are similar when we double sort on LTD and cokurtosis, coskewness and downside beta. The results are displayed in the appendix in table 17, 18 and 19, respectively. We may note that we have statistically significant positive one-month-ahead returns in the long-short portfolios in quintile two and three of cokurtosis and quintile one of coskewness.

Next we investigate the impact of using equal-weighted portfolios as opposed to value-weighted portfolios when we calculate the average one-month-ahead returns for different quintiles sorted on LTD. The results are displayed in 20 in the appendix. The results mirror those of table 5. There is a monotonic increase in one-month-ahead returns as we move from portfolios of stock exhibiting weak LTD to portfolios of stock exhibiting strong LTD, with the exception of the highest quintile exhibiting slightly lower returns than the second highest quintile. Within all quintiles the returns are statistically distinguishable from zero, but the most interesting portfolio, namely the long-short portfolio of strong-weak LTD stocks, exhibits returns that are not. We refer to table 21, 22, 23 and 24 for equal-weighted one-month-ahead portfolio returns of double sorts on LTD and beta, cokurtosis, coskewness and downside beta, respectively. The results are in line with the results for value-weighted portfolios.

Finally, we have run regressions using LTD derived from the copula specifications that minimized the negative log-likelihood functions used in the optimization part of the LTD estimation step. The results are displayed in the appendix in table 25 and 26 and are similar to the previous regression results. One should note that the coefficient estimates on LTD are slightly dimished, though still both economically and statistically significant.

5.2 Implications

The results in Section 4 are robust to changing the optimal copula specification selection criterion and to using equal-weighted as opposed to value-weighted portfolios in the portfolio sorts analyses. One could interpret the results of this study as evidence that it is possible, in the absense of frictions, to earn an LTD risk premium by investing in stocks exhibiting strong LTD. If we further believe in expected utility theory, this can be interpreted as evidence that investors are indeed averse to being exposed to stocks with higher levels of LTD. This is evidence that investors behave in accordance with the theoretical predictions in Chabi-Yo, Ruenzi, and Weigert (2018). However, there is notable statistical uncertainty in the estimates above, and the economic significance of the estimates is small when we look at sorted long-short portfolios of strong LTD minus weak LTD stocks. The regression analyses provides evidence that there is a notable economically significant impact of LTD on one-month-ahead returns.

6 Conclusion

The results of this study are somewhat in line with what has been documented for the American stock market and the German stock market, by Chabi-Yo, Ruenzi, and Weigert (2018) and Supper, Irresberger, and Weiß (2020), respectively, though slightly less unambiguous. There appears to be a risk premium for investing in stocks that exhibit a high tendency to perform especially poorly when the market crashes. Sorting stocks into quintiles based on their estimated LTD and calculating average one-month-ahead returns, we find a near monotonic increase in value-weighted portfolio returns as a function of LTD quintile. Further, there is a positive difference between the returns of portfolios of stocks that exhibit strong LTD and stocks that exhibit weak LTD, though this difference is neither statistically significant nor of a notable economic magnitude. The results are less clear when we analyse the data by sorting first on different variables and then on LTD. Turning to a multivariate analysis, we find both an economically and statistically significant association between one-month-ahead returns and LTD. This association is stable across all our regression specifications. Further, our results are robust to different portfolio formations when performing portfolio sorts analyses and to different copula selection criteria in the regression analyses.

7 Appendix

7.1 Data definitions

Table 16:
Data definitions

This table summarises the definitions of the main variables used in this study.

Variable	Definition	Data source
$r_t/r_m/r_f$	Return at time t/market return/risk-free rate, the two first in excess of the risk-free rate.	TDS, Estimated
LTD	Lower tail dependence coefficient of individual stock returns and market returns. The coefficient is estimated on daily data with 12 month rolling windows. The estimation frequency is 1 month.	TDS, Estimated
β	Covariance between excess stock return and excess market return. Calculated on monthly data.	TDS, Estimated
β^-	Downside beta estimated on daily return data from one year, following Ang, Chen and Xing (2006). It is the the same as β, but calculated conditional on return observations exceeding the mean of the market return observations.	TDS, Estimated
β^+	Upside beta estimated on daily return data from one year, following Ang, Chen and Xing (2006). It is the the same as β, but calculated conditional on return observations being lower than the mean of the market return observations.	TDS, Estimated
Coskewness	The coskewness of the daily return of a stock with the market.	TDS, Estimated
Cokurtosis	To cokurtosis of the daily return of a stock with the market	TDS, Estimated
size	The logarithm of market capitalization	TDS, Estimated
bookmarket	Book value divided by market capitalization, where book value is calculated as Total Assets minus Total Liabilities	TDS, Estimated
HML	The High minus Low factor from Fama and French (1993). Calculated from monthly data from TDS.	TDS, Estimated
SMB	The Small minus Big factor from Fama and French (1993). Calculated from monthly data from TDS.	TDS, Estimated

7.2 Constructing the Fama-French factors

Thomson Reuters Datastream (TDS) is the data source for the raw data used to construct the Fama-French factors. Landis and Skouras (2021) find that, on US data, TDS factors are statistically and economically indistinguishable to standard Fama-French CRSP factors. They also point out that there are differences when comparing international factors created using TDS data to publicly available international factors, but it is not clear whether such differences arise from poor data quality in the TDS database, poor data quality in other databases or methodological issues. All time series data stretch from the beginning of January 1997 through December 2021. We used the same constituent lists as listed at the beginning of this section.

The relevant time series variables from TDS are Common Shares Outstanding (WC05301), Total Assets (WC02999), Total Liabilities (WC03351), Price (P) and Total Return Index (RI), where the TDS variable codes are given in parentheses. The relevant static variables from TDS are Time (TIME), Currency (ECUR), Type of Instrument (TYPE), Geographic Group (GEOG) and Inactive Date (WC07015). Time contains the date of a stock's last data update. All stocks with a Time value further back than the January of 1997 were excluded from the sample. Further, we kept only stocks with a Type of Instrument variable equal to EQ, i.e. we only kept equities. To remove foreign listings, we only kept stocks with a geographical code or currency corresponding to the country of the index from which the relevant constituent lists were formed.

Having filtered the static data, we kept only time series data for the companies that remained in the static sample. For each stock, we removed all time series data more recent than the Inactive Date. This is important for the following reason. TDS provides full time series for all stocks in the sample, but some stocks have been delisted prior to the current date. For delisted stocks, the last known data point is recycled for all dates following the delisting. Hence, not removing such observations may impact later results significantly. We also removed all stocks missing available data for one or more of the time series variables of interest. Applying all these filters, we were left with 1849 companies in the sample.

Lastly we checked the data for extreme return observations, having first converted all variables except Common Shares Outstanding to Euros using the same exchange rates as described previously in this section. There were not many, but we identified 32 return observations exceeding 300%. It is not clear whether such observations stem from erroneous data or whether they are just high returns. There were also 34 return observations below -80%. Instead of removing any such large returns, we opted to winsorize the data at the 0.001 and 0.999 percent level. The reason for this is twofold. Firstly, as these returns are very few compared to the total number of return observations (189,454), the impact of doing this should not be that big. However, if the returns are not erroneous, we do not wish to exclude them from the sample. Secondly, even if such observations are few, observations that are large in magnitude can have an effect on estimates conducted using the ordinary least squares method. As the Fama-French factors are not meant to capture extreme returns, we therefore choose to winsorize as explained above.

To calculate the Fama-French factors HML and SMB we proceed in the following manner. In June of every year we define breakpoints for size and book-to-market values based on data available in the previous year. The size breakpoint is given by the yearly sample market capitalization median while the book-to-market breakpoints are given by the 30th and 70th book-to-market percentiles. In Fama and French (1993) the size breakpoints are given by the 10th and 90th percentiles of market capitalization. However, in Fama and French (2015), they use the sample median of market capitalization, though they perform a more detailed portfolio sort then what will be described below. We choose to use the median to retain a large number of companies in each portfolio sort. As the authors themselves note in the Fama and French (1993), the choice of breakpoints is arbitrary. The aim of the portfolio sorts is to create factors that are more or less independent of each other.

Intersecting the different portfolio sorts, we obtain six portfolios: S/H, S/N, S/L, B/H, B/N and B/L, where the S and B are the size sorts small and big and H, N and L are the book-to-market sorts high, neutral and low, respectively. The portfolios are then value-weighted according to market capitalization and monthly returns are calculated starting from July and through June next year. The factor returns are then calculated as

$$HML = \frac{1}{2}(S/H + B/H) - \frac{1}{2}(S/L + B/L), \tag{13}$$

and

$$SMB = \frac{1}{3}(S/L + S/M + S/H) - \frac{1}{3}(B/L + B/M + B/H). \tag{14}$$

The sample Pearson correlation between the two factors is 0.18, which is quite low. Further, this correlation is reduced to close to 0 if we remove one common observation that has a significant impact on the sample correlation. Visually inspecting a scatterplot of the two factors, which for brevity is not included here, the observations form a cloud with no easily discernible pattern. We interpret this as evidence that the factors do not exhibit any significant degree of dependence.

To gauge the extent to which our data sample is representative for the Nordic countries, we performed a simple comparison with the MSCI Nordic index.[2] We calculated value-weighted index returns from our sample and calculated its Pearson correlation with the MSCI Nordic index returns, the result of which was a correlation coefficient of 0.978. In Section 2 we noted some weaknesses of using Pearson correlation as a measure of statistical dependence between random variables, but such a high correlation is still evidence that our data sample is representative for the Nordic countries. The different index returns are not exactly equal, though close, but visually inspecting a scatterplot between the two index returns it is clear that the indices behave very similarly. One should not expect the returns to be exactly similar in

[2] https://www.msci.com/documents/10199/6bd9ad54-61be-4bdf-afcd-7465994bcb95

magnitude as at the time of writing the MSCI Nordic index consisted of only 85 constituents, which MSCI states covers approximately 85% of the free float-adjusted market capitalization in each country. We therefore have confidence that this data sample is suited to quite accurately describe the Nordic markets.

7.3 Robustness tables

Table 17:
Future returns sorted on cokurtosis and LTD

Stocks have been sorted into quintiles based on their estimated cokurtosis and LTD, but using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied cokurtosis and/or LTD values, the first observation with that cokurtosis/LTD value is ranked lower than the following observation with the same cokurtosis/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low Cokurtosis	2	3	4	5 High Cokurtosis
1 Weak LTD	0.466%	0.709%**	0.359%	0.519%	0.704%
2	0.28%	0.876%***	0.598%*	0.297%	0.433%
3	0.567%**	0.577%**	1.135%***	0.028%	0.278%
4	0.404%	1.387%***	0.595%	0.753%*	0.574%
5 Strong LTD	0.813%**	1.316%***	1.145%***	0.731%*	0.568%
Strong - Weak	0.347%	0.608%**	0.786%*	0.211%	-0.137%

Table 18:
Future returns sorted on coskewness and LTD

Stocks have been sorted into quintiles based on their estimated coskewness and LTD, but using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied coskewness and/or LTD values, the first observation with that coskewness/LTD value is ranked lower than the following observation with the same coskewness/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low Coskewness	2	3	4	5 High coskewness
1 Weak LTD	0.637%*	0.723%*	0.642%	0.555%	0.374%
2	0.63%*	0.967%***	0.921%***	0.046%	0.477%
3	0.685%*	0.729%***	0.971%***	0.445%	-0.343%
4	1.166%***	0.927%***	0.944%***	0.376%	0.487%
5 Strong LTD	1.233%***	1.029%***	1.018%***	0.664%	0.405%
Strong - Weak	0.596%**	0.307%	0.376%	0.109%	0.031%

Table 19:
Future returns sorted on downside beta and LTD

Stocks have been sorted into quintiles based on their estimated downside beta and LTD, but using the optimized negative log-likelihood function as a decision criterion for choosing the optimal copula specification. For each quintile, a value weighted return for month *t+1* has been calculated using weights from month *t*. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied downside beta and/or LTD values, the first observation with that downside beta/LTD value is ranked lower than the following observation with the same downside beta/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low β^-	2	3	4	5 High β^-
1 Weak LTD	0.196%	0.247%	1.203%***	0.622%	0.471%
2	0.373%*	0.405%	0.813%**	0.607%	-0.036%
3	-0.021%	0.976%***	0.553%	1.025%***	0.662%
4	0.133%	0.6%**	1.204%***	0.931%**	0.707%
5 Strong LTD	0.302%*	1.289%*	1.162%***	0.663%*	0.82%*
Strong - Weak	0.107%	1.042%	-0.041%	0.041%	0.349%

Table 20:
Future returns sorted on LTD

Stocks have been sorted into quintiles based on their estimated LTD. For each quintile, an equal weighted return for month *t+1* has been calculated. This gives 1 time series per quintile of value weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied LTD values, the first observation with that LTD value is ranked lower than the following observation with the same LTD value. This pattern repeats in the presence of more than two ties.

Quintile	Returns	P-value
1 Weak LTD	0.658%*	0.078
2	0.815%***	0.009
3	0.871%***	0.007
4	1.117%***	0.003
5 Strong LTD	0.991%**	0.027
Strong - Weak	0.333%	0.144

Table 21:
Future returns sorted on beta and LTD

Stocks have been sorted into quintiles based on their estimated beta and LTD. For each quintile, an equal weighted return for month *t+1* has been calculated. This gives 1 time series per quintile of equal weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied beta and/or LTD values, the first observation with that beta/LTD value is ranked lower than the following observation with the same beta/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low β	2	3	4	5 High β
1 Weak LTD	0.545%*	0.907%***	0.954%**	1.19%**	0.831%
2	0.494%**	0.673%**	1.059%***	1.293%***	0.972%*
3	0.55%**	0.704%**	1.108%***	0.855%*	0.99%*
4	0.508%**	0.83%**	1.119%***	1.111%***	0.789%
5 Strong LTD	0.754%***	0.893%***	1.269%***	1.064%***	0.785%
Strong - Weak	0.208%	-0.014%	0.315%	-0.126%	-0.045%

Table 22:
Future returns sorted on cokurtosis and LTD

Stocks have been sorted into quintiles based on their estimated cokurtosis and LTD. For each quintile, an equal weighted return for month *t+1* has been calculated. This gives 1 time series per quintile of equal weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied cokurtosis and/or LTD values, the first observation with that cokurtosis/LTD value is ranked lower than the following observation with the same cokurtosis/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low Cokurtosis	2	3	4	5 High Cokurtosis
1 Weak LTD	0.506%	1.027%***	1.031%**	0.796%*	0.523%
2	0.549%*	1.104%***	1.104%***	0.767%*	1.035%**
3	0.64%**	1.039%***	1.106%***	0.754%*	1.004%**
4	0.364%	1.23%***	1.011%***	0.564%	0.944%**
5 Strong LTD	1.004%***	1.346%***	1.226%***	0.853%*	0.705%
Strong - Weak	0.498%**	0.319%	0.195%	0.057%	0.182%

Table 23:
Future returns sorted on coskewness and LTD

Stocks have been sorted into quintiles based on their estimated coskewness and LTD. For each quintile, an equal weighted return for month *t+1* has been calculated. This gives 1 time series per quintile of equal weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied coskewness and/or LTD values, the first observation with that coskewness/LTD value is ranked lower than the following observation with the same coskewness/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low Coskewness	2	3	4	5 High Coskewness
1 Weak LTD	1.034%***	1.163%***	0.973%***	0.718%*	0.511%
2	1.059%***	1.277%***	1.016%***	0.349%	0.577%
3	0.89%**	1.089%***	1.042%***	0.547%	0.656%
4	0.847%**	1.168%***	1.137%***	0.528%	0.545%
5 Strong LTD	1.11%***	1.183%***	1.349%***	0.905%*	0.581%
Strong - Weak	0.075%	0.02%	0.376%	0.186%	0.07%

Table 24:
Future returns sorted on downside beta and LTD

Stocks have been sorted into quintiles based on their estimated downside beta and LTD. For each quintile, an equal weighted return for month *t+1* has been calculated. This gives 1 time series per quintile of equal weighted portfolio returns in month *t+1*. The column 'Returns' report the time average of these series. *, ** and *** indicate statistical significance at, respectively, the 10%, 5% and 1% significance level.
Note that in the presence of tied downside beta and/or LTD values, the first observation with that downside beta/LTD value is ranked lower than the following observation with the same downside beta/LTD value. This pattern repeats in the presence of more than two ties. T-statistics for all the hypothesis testing have been calculated using Newey and West (1987) standard errors.

Quintile	1 Low β^-	2	3	4	5 High β^-
1 Weak LTD	0.421%	0.983%***	1.201%***	1.164%**	0.955%
2	0.384%*	0.839%**	1.184%***	1.256%***	1.269%**
3	0.122%	0.881%***	0.933%**	0.916%**	0.99%*
4	0.121%	0.746%**	1.289%***	1.194%***	0.815%
5 Strong LTD	0.303%	1.001%***	1.279%***	1.104%***	0.906%
Strong - Weak	-0.119%	0.018%	0.078%	-0.061%	-0.049%

Table 25:
Multivariate regression results

Regression of one-month-ahead returns on different sets of control variables. Note that LTD has been derived from the copula specifications that minimized the negative log-likelihood functions in the optimization step of the LTD estimations. The dependent variable is the one-month-ahead return. (1) is a univariate regression on LTD, (2) is a bivariate regression on LTD and beta, (3) is a multivariate regression on LTD, beta and downside beta, and (4) is a multivariate regression on LTD, beta, downside beta and upside beta. In (5) we omitted beta since it is quite highly correlated with upside beta and downside beta. This does not change the estimated coefficient on LTD. Standard errors are clustered on months.

Dependent Variable:			r_{t+1}		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(Intercept)	0.0055^{**}	0.0052^{**}	0.0047^{**}	0.0047^{**}	0.0047^{**}
	(0.0026)	(0.0022)	(0.0019)	(0.0019)	(0.0019)
LTD	0.0241^{***}	0.0234^{***}	0.0209^{**}	0.0209^{***}	0.0209^{***}
	(0.0081)	(0.0086)	(0.0082)	(0.0080)	(0.0080)
β		0.0010	-0.0007	-0.0007	
		(0.0051)	(0.0065)	(0.0092)	
β^-			0.0023	0.0022	0.0021
			(0.0035)	(0.0035)	(0.0030)
β^+				-2.38×10^{-5}	-0.0005
				(0.0067)	(0.0050)
Fit statistics					
Observations	185,660	185,660	185,660	185,660	185,660
R^2	0.00132	0.00134	0.00142	0.00142	0.00142
Adjusted R^2	0.00131	0.00133	0.00140	0.00140	0.00140

Clustered (date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 26:
Multivariate regression results

Regression of one-month-ahead returns on different sets of control variables. Note that LTD has been derived from the copula specifications that minimized the negative log-likelihood functions in the optimization step of the LTD estimations. The dependent variable is the one-month-ahead return. (1) is a multivariate regression on LTD, beta, downside beta, upside beta and coskewness. For each regression, we add one control variable. In (2) we add cokurtosis. Standard errors are clustered on months. In (3) we add size which is the logarithm of market capitalization, and in (4) we add the book to market ratio.

Dependent Variable:		r_{t+1}		
Model:	(1)	(2)	(3)	(4)
Variables				
(Intercept)	0.0046**	0.0045**	0.0249***	0.0200***
	(0.0019)	(0.0019)	(0.0070)	(0.0066)
LTD	0.0193***	0.0186***	0.0221***	0.0225***
	(0.0073)	(0.0071)	(0.0076)	(0.0076)
β	-0.0022	-0.0028	0.0028	0.0023
	(0.0090)	(0.0090)	(0.0096)	(0.0096)
β^-	0.0028	0.0029	-0.0003	-0.0005
	(0.0034)	(0.0034)	(0.0038)	(0.0038)
β^+	0.0012	0.0017	-0.0027	-0.0026
	(0.0065)	(0.0065)	(0.0071)	(0.0071)
Coskewness	-0.0034*	-0.0049*	-0.0081**	-0.0080**
	(0.0020)	(0.0027)	(0.0036)	(0.0036)
Cokurtosis		0.0009*	0.0013**	0.0013**
		(0.0005)	(0.0006)	(0.0006)
size			-0.0012**	-0.0010**
			(0.0005)	(0.0005)
bookmarket				0.0026***
				(0.0007)
Fit statistics				
Observations	185,660	185,660	70,245	70,245
R^2	0.00171	0.00186	0.00334	0.00419
Adjusted R^2	0.00168	0.00183	0.00324	0.00407

Clustered (date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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