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Systemic Risk Within and Across the Banking and Insurance Sectors in Times of Stress:

A study of Scandinavia

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Abstract:

My master's thesis aims to replicate the study by Schoenmaker, Slijkerman and de Vries (2005) but using different country data and observation period. The aim is to see how the systemic risk measure developed by Schoenmaker et al. fares when we include a geographically smaller region which experienced a financial crisis in the early years of the 1990s and which has felt the effects of the current financial crisis. Also, dead stocks are included in the study not only to avoid selection bias but also to observe whether the systemic risk measure captures dependencies when we are no longer only observing extreme returns as proxies for default events, but when such an event actually takes place. To capture changes in systemic risk, the sample period 1987-2010 is divided into two periods: 1987-1996 and 1997-2010. In addition estimates of systemic risks are also reported for the years 1992-2003 in order to compare with the results of Schoenmaker et al. (2005).

Acknowledgements

The master's thesis in front of you is the result of months of labour and quite a bit of hurdles. Difficulties which I managed to overcome with the help of my supervisor Prof. C. G. de Vries and my partner Pepijn Nijhuis. I would like to thank both ever so much for their patience and good advice. Getting back into education and making a change in career was a difficult decision but the right one. I would like to thank some of my previous working colleagues for having given me the courage to do so: Dorota Borowiecka, Conni Ridolph and Adriana Quijada. Special thanks to go Dr. Erwin van Sas and Dr. Jaap Bos for their encouraging words during my Bachelor in Economics at Utrecht University. In addition, I am utterly grateful for the unquestionable love and moral support given to me by my family: Pepijn, Margarita, Samantha and Antonia. Without any of you none of this would have been possible.

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Maureen Loyola Leyton

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1 Introduction

The aim of this thesis is to replicate the work of de Vries, Schoenmaker and Slijkerman (2005) into downside risk in the financial sector in Europe and to explore whether systemic risk in Scandinavia was different than that in Europe. I will complement the Schoenmaker et al. (2005) study by I using a different time period and data from another geographical location than that of the original study. To this end, I will use stock return data of a selection of financial entities for the period 1987 until today as I try to measure the level of interdependencies within and cross bank and insurance sectors in times of stress. Start and end dates are chosen to capture the 1990s financial crisis witnessed in Scandinavia and the effects of the current financial crisis respectively. The systemic risk measure devised by Schoenmaker et al. (2005) uses Extreme Value Theory (EVT) which not only allows to deal with the non-normal distribution nature of assets' returns but has the added benefit of studying solely what happens in the tails of distributions.

The onset of the latest financial crisis has yet again put an emphasis on the importance of estimating systemic risk. Stability of the financial sector is undeniably important for a number of reasons. First, banks are very important for the entire economy as they play a key role in the functioning of the payment systems. Second, banks perform the paramount function of financial intermediation and matching contrasting demands of savers and borrowers. Finally, when carrying out their financial intermediation, banks reduce the information asymmetry that would exist had savers and borrowers had to transact at arm's length. These reasons are often quoted as the motive for banks having received substantial more attention than insurance companies, and why banks have been at the receiving end of support measures during periods of stress. Also, systemic risk has been measured to be lower among insurers than among banks and there is no history of insurance runs as there is a history of bank runs. Insurance companies are also financial intermediaries and they too have an important role channelling wealth from one generation to another and as banks they channel savings into investments (see Matthews and Thomson, 2008, Ch. 3, and Millon Cornett and Saunders, 2008, Ch 1). Maintaining financial stability of financial institutions is, in other words, essential to prevent negative externalities of their activities to the rest of the economy. Hence the need for regulation.

A broad definition of systemic risk is the risk of one financial institution in trouble transmitting its difficulties to another financial institution. Such risk stems from the fact that banks and insurances are linked with each other through common exposures. For banks, one source of common exposure is the fact that, in an attempt to diversify portfolio risk, banks enter into other activities than their core activities. This results in banks having more common exposures. Another source for banks comes from banks being connected with one another by issuing syndicated loans. These loans arise in instances where the loan amount to a single borrower is so large, that a number of banks end up issuing the sum of the credit. Two final sources that could be mentioned are the deposits that banks hold in one another and the short-term lending banks issue one another (or the money market). The interest rate charged in the money market is indirectly but nevertheless determined by the central banks who control the marginal lending rate. Money market rates are thus a common exposure banks face, and is entirely outside the control of the banks. Insurers are also exposed to common risk factors within their industry. One example thereof are reinsurance activities where banks take out insurance from a reinsurer for credit risk the insurer is not willing to bear. More recent developments in financial engineering has meant that credit default risk can be transferred into insurance risk via credit default swaps (Schoenmaker et al., 2005). Similarly, securitization has provided yet another vehicle for diversification of risk. Default risk of loans is effectively shifted to other entities in the capital markets (Matthews and Thomson, 2008, Ch. 9). In summary, within and across the banking and insurance sectors we find common exposures in both the asset and liabilities side of their balance sheets which, in turn, increase systemic risk (de Vries, 2004 and Millon Cornett and Saunders, 2008, Ch 1).

This thesis is organized as follows. In section 2, I will offer a literature review covering past studies into systemic risk and studies which offer a suitable backdrop to the results of this paper. In section 3, I will discuss return distributions of the data used in this paper, paying particular attention to the tails of the distributions. I follow up by revisiting the study by Schoenmaker et al. (2005) in section 4. There, the two measures (univariate and multivariate) for systemic risk and their derivations are presented. Before introducing and discussing empirical results in section 6, an account of the financial crises experienced in Scandinavia, in the early 1990s and the current one, is given on section 5. The intention of this is to give the reader a factsheet with which to study the empirical results of section 6. Finally, in section 6, I provide a conclusion of the outcomes of this study. As the study involves a substantial amount of empirical work, the main body of this thesis covers and discusses the most important elements thereof. The empirical appendix on section 8 offers a detailed description of the data selection process, general summary statistics, a detailed description of the methodology used in the empirical tests, comprehensive test results and a subsection on how to replicate the results.

2 Literature review

Central to by the study by Schoenmaker et al. (2005) and to this thesis are dependencies between variables but specifically, dependencies at the tails. Large proportion of past studies into dependencies have used the correlation coefficient as a yardstick for measuring dependency. Yet many scholars have pointed out the fact that correlation based tests rest on the assumption of normality of return distributions. More often than not, this is not the case. The returns of this thesis are an example thereof. Section 3 of this paper offers a closer examination of the characteristics exhibited by the data used in this study. Another criticism of the correlation coefficient is that it is driven by the observations in the centre of the distribution. In fact, when financial stability is of interest, most would not focus on what happens when economic conditions are at stable levels or, in other words, what happens at the centre of return distributions. On the contrary, one would focus on what happens in extreme negative events, thus at the left tail of a distribution. Therefore, for the work of regulators, relying on correlation coefficients is not very informative. An additional concern about the correlation coefficient is that correlation can actually be zero in instances where, in fact, there is a relationship that is not linear but that is a relationship nevertheless (Newbold, 2007). EVT, on the other hand, studies the extremes of distributions. Hence, EVT offers a framework in which it is possible to focus on the study of negative extreme events. In what remains of this section, I will offer a review of a selection of past studies whose focus has been on crisis events and comovements and I will discuss their outcomes.

Forbes and Rigobon (2002) study contagion from one market to another. To this effect they use stock market returns realized during different crisis events at a range of geographical locations. These are: the East Asian Crisis of 1997, the 1994 Mexican Peso Crisis and the 1987 U.S. Stock Market Crash. They correctly point out that studies into contagion which base themselves on correlation coefficient estimates are biased upwards. When market volatility increases, the correlation between two market returns also increases. Therefore the correlation coefficient is biased upwards.[1] The authors show how to quantify this bias and correct for it. The correlation coefficient without this correction is referred to as the conditional correlation (conditional on market volatility) and the one including this correction is referred to as the unconditional correlation. When contagion is defined as a statistically significant increase of the correlation coefficient following a crisis event, the estimates show that the unconditional correlation coefficient does not increase significantly from a stable period to a crisis period. Thus there is no evidence of contagion rather of interdependencies in all the three events they study. The study of Forbes and Rigobon (2002) exposes the drawback of the correlation coefficient when studying relationships between variables. One could possibly extend the results of Forbes and Rigobon to this thesis. By looking at returns during crises, the authors are looking at a tail distribution. They thus find dependencies at the tails. Although the results are not exclusively for the financial sector, rather for a combination of sectors.

Longin and Solnik (2001) study market return data for a combination of market returns: U.S./United Kingdom., U.S./France, U.S./Germany and U.S./Japan. In contrast to Forbes and Rigobon (2002), the authors say correlation is not conditional on market volatility but on the condition (or trend) of the market. They find that, during a bust, correlation increases significantly and is stable in booms.[2] Thus in Forbes and Rigobon (2002) the upward bias is due to heteroskedasticity in market returns whereas in Longin and Solnik (2001) the increase in correlation is due to the spurious relation between correlation and volatility. With help of EVT they then model the tail distributions and calculate the conditional correlation (conditional on return volatility). The authors then show that return data at the extremes of return distributions does not follow a normal distribution. They then generate random normal distributed variables using the means and covariances of the underlying real data. Conditional correlation coefficients are reported using a threshold range from -10 to +10 percentage points. The outcome is that conditional correlation between returns is higher for the real data for return exceedances at the lower end of the threshold range (bear market) than for return exceedances at the higher end of the threshold range (bull market). For the bivariate normal distributed data, conditional correlation is low at the upper and lower end of the threshold range, but increases towards the middle of that range. The latter is in line with what I see and discuss in section 4.2.2 on downside dependence for the bivariate normal case.

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[1] The definition for the correlation coefficient is: $\rho_{X,Y} = Cov(X,Y)/(\sigma_X \sigma_Y)$. When explaining this upward bias, the authors assume no omitted variables nor endogeneity and following several manipulations of equations, they arrive at the following expression of correlation: $\rho_{X,Y} = \beta\, \sigma_x/\sigma_y$, where β is a coefficient in $y_t = \alpha + \beta x_t + \epsilon_t$, y_t and x_t are returns in two separate markets and ϵ_t is an error term. They also show how the ratio σ_x/σ_y is higher in high market volatility periods than in low volatility ones and that therefore the correlation coefficient is higher in higher volatility periods than in lower volatility ones.

[2] The increase is found to be statistically significant.

Clare and Priestley (2002) do not use EVT in their univariate approach to study the probability of failure of Norwegian banks over the time period 1980-1995, a time which saw: financial deregulation, a financial crisis and a recovery period. The authors used a market-based approach (CAPM) and a multivariate Generalized Autoregressive Conditional Heteroscedastic in Mean (AGARCH-M) model to estimate $\sigma_{e_{it}}$ in their measure for firm probability of failure: $1/\sigma_{e_{it}}$. Where the subscript i stands for stock i and $\sigma_{e_{it}}$ is the standard deviation of a white noise term of the CAPM. They use monthly excess return data and calculate the probability of failure of the banking industry and that of a wider market index. The authors find that the probability of failure across the banking industry increased during the period of deregulation and deteriorated further by the time of the financial crisis and subsequently, in 1995, recovered to initial levels. The probability of failure for the wider market index does not follow this path and rather fluctuates around the same stable levels throughout the time period of study. This the authors interpret as no evidence of contagion effects from the banking sector to other industry sectors. Within the banking sector though, individual banks' plots of $1/\sigma_{e_{it}}$ show the same pattern of the probability of failure as the one for the banking industry as a whole. The authors interpret this as evidence of contagion within the banking sector. The outcomes of this study though are based on lower frequency data than the one used in this thesis. Therefore, and because of its different approach, the estimates presented in the Claire and Priestley (2002) paper would not only suffer from high variance but they would also not be entirely comparable with results presented in section 6 of this thesis. Nevertheless the authors' findings provide with useful insights for this thesis.

Complementing the literature available on contagion risk is the study by Hartmann, Straetmans and de Vries (2005). They use EVT, the tail-βs method and excess returns of bank stocks for 25 euro area and 25 U.S. ones from 1992-2004 to study spillover risk between banks within a region, country and across regions, and banks' exposure to aggregate shocks proxied by banking sector market indices and high-yield bond spreads. They also test whether these two types of risks have evolved over time. The measure devised for multivariate spillovers is the same as the one in Schoenmaker et al. (2005) and that is revisited in section 4.2.5 of this thesis. But Hartmann et al. (2005) apply this measure to a setting where there are more than two companies. The tail-β measure is the same as the measure for the multivariate bank setting but applied to a bivariate setting, thus as in Schoenmaker et al. (2005). In this setting, bank excess returns are conditioned on the market index or the high-yield spread. Here follows a selection of the findings of this study that are of interest to this thesis. For the euro countries, systemic risk is larger nationally than across nations. This result is for a large proportion of the sample (large banks located in central Europe) statistically significant. For those cases where this is not the case, systemic risk is equal nationally and across borders. In these cases, the authors suggest that supervision with an international focus could be in place. In addition, in the euro countries, systemic risk has increased both within and across borders. In the euro country sample, the smaller banks in large countries and those in relatively remote or small sized countries were less vulnerable to aggregate shocks than large banks in large countries and large banks active in a large area (exhibiting low tail-βs versus high tail-βs respectively). High-yield spread is found to be of no influence to systemic risk of the banking sector.

Outcomes of the studies covered above are a useful backdrop to the results of this thesis. Building up to that moment, the next section will lay out the specific characteristics of the data included in the samples of this thesis and will argue that these returns are not normal distributed.

3 Returns of financial institutions are fat-tailed.

As mentioned in the introduction, the systemic risk measure developed by Schoenmaker et al. (2005) is particularly well-suited for non-normally distributed variables. Stocks' returns are widely documented not to follow a normal distribution. This observation is confirmed when I look at the distributions of the entities included in this thesis. See Table 11 on section 8.2 in the empirical appendix for the Eviews-generated summary statistics for all three sample periods. In that table, we see that all return distributions are either negatively or positively skewed. In other words, these returns are not symmetrically distributed around the mean as is the case in a normal distribution.[3] All skewness values are non-zero. The values for kurtosis are also not three as is the case for a normal distribution.[4] Thus the return distributions of the samples display fat tails. Eviews even performs a Jarque-Béra test of normality.[5] The results of this test are also included in the summary statistics and with p-values below 5% all entities in each of the sample periods reject the null-hypothesis of normality. In summary, the data used in this thesis also lines up with the widely accepted notion that high-frequency – in this case daily – financial data is hardly ever normally distributed.

Figure 1 below shows, for the sample period 1997-2010, the left tail of a histogram of the return distribution of the Norwegian bank DnB NOR. The over-imposed hypothetical distributions are for a normal (in red) and for a student-t distribution (in green) with 3 degrees of freedom. Returns are calculated as:

$$ln\left(\frac{RI_t}{RI_{t-1}}\right)$$

Where:

RI_t: return index value on date *t*

RI_{t-1}: return index value on date *t-1*

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[3] Skewness is also the third central moment which in fact are just the cube deviations from the mean standardized. The sample skewness is thus:

$$Skew = \frac{\sum(x-\bar{x})^3}{(1/n)\ [\sum(x-\bar{x})^2]^{3/2}}$$

Where:

$\bar{x}$: is the sample mean

x: is one observation value

n: are the number of observations

[4] Kurtosis measures how peaked a distribution is. For a normal distribution the value is 3. The higher the kurtosis the more likely an extreme return is to occur. The measure is also known as the fourth central moment and its definition is:

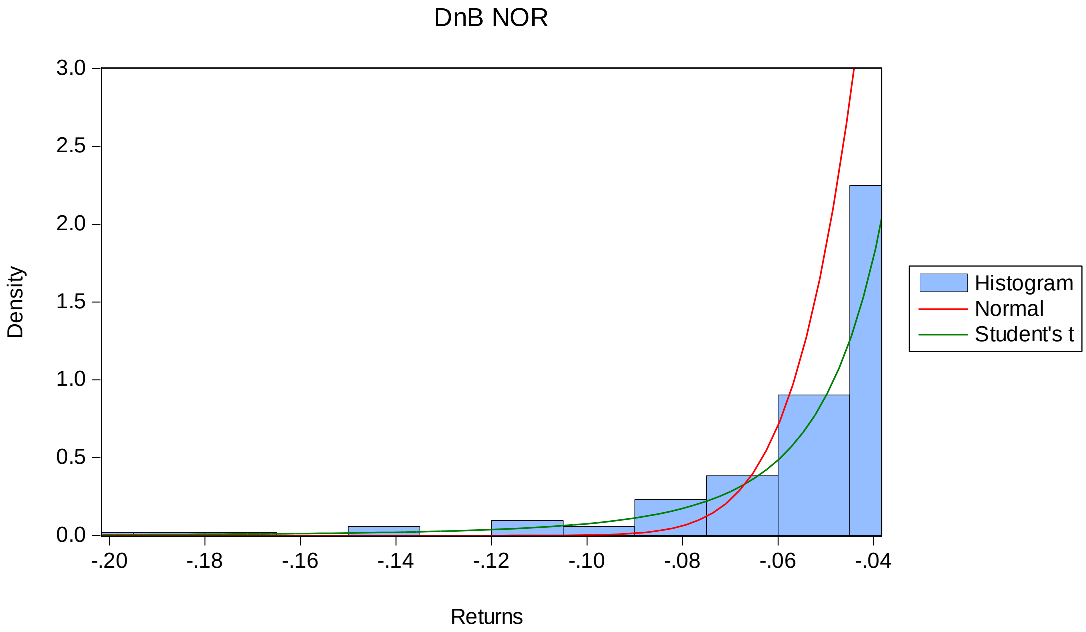
$$Kurt = \frac{\sum(x-\bar{x})^4}{(1/n)\ [\sum(x-\bar{x})^2]^2}$$

[5] Jarque-Béra test statistic is defined as:

$$JB = \frac{n}{6}\left(skew^2 + \frac{1}{4}(kurt-3)^2\right)$$

Figure 1 illustrates that, at the tails of the return distribution, financial returns are closer to a student-t distribution than to a normal one.

Figure 1 – Histogram of returns with theoretical distributions overimposed, 1997-2010 sample and raw data*



* The overimposed student-t distribution has 3 degrees of freedom.

3.1 Hill estimator

Another way to estimate the thickness of distribution tails is by calculating the Hill estimator ($\hat{\alpha}$). $\hat{\alpha}$ is also referred to as the tail index estimate for the distribution of a sample and for fat tailed distributions it typically has a value of 3. It is defined as follows:

$$\hat{\xi}_{m,n}^{(H)} = \hat{\alpha}^{-1} = \frac{1}{m}\sum_{j=1}^{m} \ln \frac{X_{(j)}}{X_{(m+1)}} \tag{1}$$

Where

n: is the total number of observations in the sample and $X_{(1)} \leq X_{(2)} \leq \cdots \leq X_{(n)}$

m: is the number of highest order statistics included in the calculation of $\hat{\alpha}$.

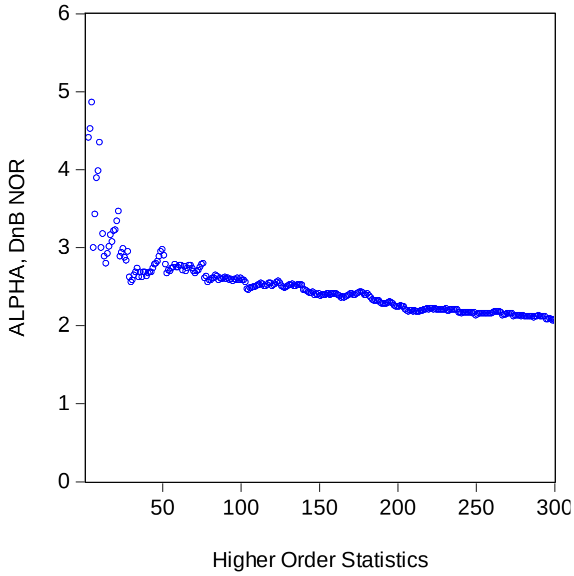
The question that remained was how to chose the correct value for m? First of all, I sorted each stock's return observations ascending, thus I calculated a series of values for $\hat{\alpha}$ for each distribution by shifting m up, step by step, and by doing so moving ever closer to the middle of the distribution. For the choice of a suitable value for m, the number of higher order statistics to include should be guided by looking for the value of m that minimizes the asymptotic mean square error (MSE).[6] This can be achieved by means of the eyeball method. This is a visual approach in which, for each company, I plot the series of $\hat{\alpha}$s against the number of higher order statistics (m).[7] An example of

[6] That minimizes the MSE of the Hill estimator.

[7] Other ways to estimate the value of m that minimizes the MSE are: by means of the Moment Estimator, Pickands estimator or the Drees-Pickand estimator (see Reich, 2004, pp. 10-11).

one such resulting Hill plot is shown in Figure 2 below.[8] I then try to identify the first plateau encountered when moving up through the higher order statistics. This is where the Hill estimator is more or less stable and we balance between too much variability of $\hat{\alpha}$ (at the very left end of the distribution) and too much one way movement where we are moving to the centre of the distribution and no longer measuring at the tail.

Figure 2 – Hill plot for DnB NOR returns and sample 1997-2010*



* The total number of return observations for DnB NOR were 3468

For this particular example, alpha is stabilizes around the 95th higher order statistic with a resulting $\hat{\alpha}$ of 2.57. This is close to 3, the typical value of a fat tailed-distribution. This is the case for most of the stocks included in the samples of this thesis. For a full list of the Hill estimators in all samples, see Table 14 in section 8.5.1 of the empirical appendix. Hence again proof that financial returns are not normally distributed.[9] In section 4 below, I will revise the systemic risk measures devised by Schoenmaker et al. (2005) and which are the heart of this thesis.

4 Base study revised: Schoenmaker et al. (2005)

As mentioned in the introduction, the base study of this thesis is Schoenmaker et al. (2005). In this section I will go over the measures developed by the authors using EVT. I will begin by presenting the univariate estimator used to calculate the probability of a stock's return exceeding a specified loss level (x_{var}). The subscript var stands for Value at Risk. I will then move on to present the multivariate estimator of the article. To this end I will go through the different steps taken by the authors to first arrive at a systemic risk measure and how they then use a reduced-form approach to illustrate how downside dependence works within and across the insurance and banking sectors. With this in mind and with the insights of Feller's theorem, they then go on to estimate a theoretical value for these dependences.

[8] For a full list of Hill plots for all entities and samples, see section 8.6 of the empirical appendix.
[9] For student-t distributed variables, the additional added insight from knowing the Hill estimator of the distribution is that the Hill estimator, in those cases, corresponds to the degrees of freedom (v) of the student-t distribution.

4.1 Univariate estimator

In section 3, I argued that returns in this thesis exhibit fat tails. This means that their cumulative distribution functions, at the extremes, have a first order condition or shape, that is identical to the Pareto distribution here below.

$$F(x) = 1 - x^{\alpha} L(x) \qquad \text{as } x \to \infty \tag{2}$$

Where $L(x)$ changes very slowly so that:

$$\lim_{t\to\infty} \left(\frac{L(tx)}{L(t)}\right) = 1, x > 0$$

In other words, at the extremes of the distribution the effect $L(x)$ on (2) above is negligible. Combining this insight with a restatement of the Pareto distribution, equation (2), means we can say that, at the extremes, the tail changes regularly:

$$\lim_{t\to\infty} \left(\frac{1 - F(tx)}{1 - (t)}\right) = x^{-\alpha} \qquad \text{where } \alpha > 0\,, t > 0$$

α is the tail index introduced in the Hill estimator discussed on section 3.1. The reported Hill estimators of each company are then used in the estimation of the univariate probability of a stock's return exceeding a specified loss level (x_{var}). Where var stands for Value at Risk. This probability is estimated by the inverse quantile estimator, equation (3) below.

$$\hat{p} = \frac{m}{n}\left(\frac{X_{m+1}}{x_{var}}\right)^{\hat{\alpha}} \tag{3}$$

Where:

n: is the total number of observations in the sample and $X_{(1)} \leq X_{(2)} \leq \cdots \leq X_{(n)}$

m: is the number of highest order statistics included in the calculation of $\hat{\alpha}$.

$\hat{\alpha}$: is the estimated tail index

X_{m+1}: is the $m + 1^{\text{th}}$ higher order statistic

As in the base article, I choose an x_{var} level at 15% (thus a 15% loss). The results are reported on Table 2 on section 6.2.

4.2 Multivariate estimation

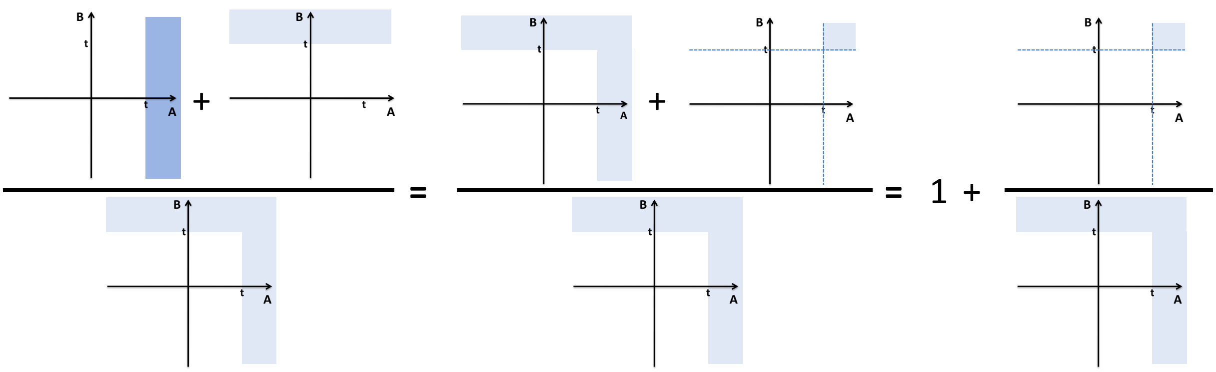
4.2.1 Systemic risk measure

The example used to arrive at the count measure for systemic risk in Schoenmaker et al. (2005), bases itself on two firms but this can easily be modified, at least with statistical software power, to apply to more than two firms. The number of firms that fail is denoted by k and A and B are the random returns generated by the two financial institutions in the economy. Expressing in conditional expectations terms, given a threshold value of t, the expected number of firms expected to fail is

$$\begin{aligned} E[k|k \geq 1] &= \frac{P(A > t, B \leq t) + P(A \leq t, B > t) + 2P(A > t, B > t)}{1 - P(A \leq t, B \leq t)} \\ &= \frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)} \end{aligned} \quad (4)$$

On the nominator we can see the sum of the joint probabilities of all possible scenarios where 1 or more firms fail (its returns are over a specified loss threshold t). That is the probability that A fails given that B does not, plus that B fails given that A does not, and the two possible outcomes where one firm fails given that the other has already failed. On the denominator is the probability that at least one firm fails. In the end the nominator can be replaced by the sum of the marginal probabilities. The end result is equation (4), the measure for systemic risk. In illustrative terms equation (4) looks like Figure 3 below.

Figure 3 – Systemic risk measure (equation 4) visualised



Source: Lecture notes from a lecture given by Prof. de Vries on the 30th March 2010 at the Duisenberg school of finance.

Thus it is possible to re-write the systemic risk equation so that, for an economy made up of only two companies, the conditional probability on a systemic crisis, given a threshold level t is equation (5) below:

$$\begin{aligned} &E[k|k \geq 1] = \frac{P(A > t) + P(B > t)}{1 - P(A \leq t, B \leq t)} = 1 + \frac{P(A > t, B > t)}{1 - P(A \leq t, B \leq t)} \Leftrightarrow \\ &\frac{P(A > t, B > t)}{1 - P(A \leq t, B \leq t)} = E[k|k \geq 1] - 1 \end{aligned} \quad (5)$$

Having devised a systemic risk measure, the authors point out that for the study of systemic risk it is observations at the extremes of return distributions that are the subject of interest. They therefore choose threshold values t that are located at the extremes, thus for sufficiently large t they contemplate the following identity:

$$SR(k) \equiv \lim_{t \to \infty} E[k|k \geq 1] \tag{6}$$

4.2.2 Downside dependence

When studying systemic risk, with the help of returns the emphasis is on extreme negative returns. As mentioned in the literature review (section 2), a lot studies into systemic risk are often based on the assumption that returns follow a normal distribution and in section 3 it was shown that it is safe to refute this assumption. The systemic risk measure in Schoenmaker et al. (2005) does not rely on the assumption of normality and only focuses on the tails of distributions.

Figure 4 below shows that the returns of two financial institutions, in this case the Swedish SE-Banken and Norwegian DnB NOR, show dependency at the tails. This is evident from the fact that the outliers line up on a diagonal line, just as observed in the sample by Schoenmaker et al. (2005).

Figure 4 – Scatter plot of return data – raw data 1997-2010

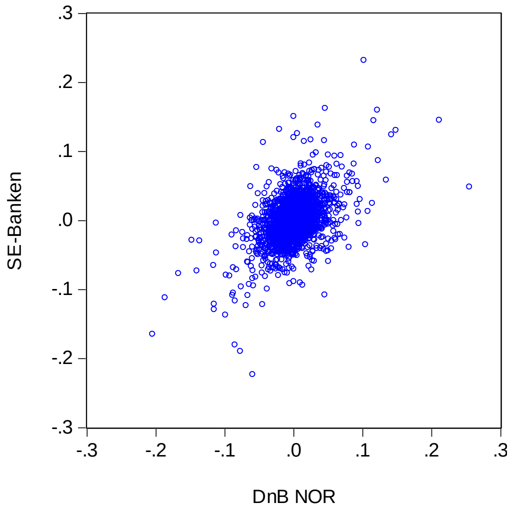


Figure 5 – Scatter plot of return data – normal distributed, 1997-2010

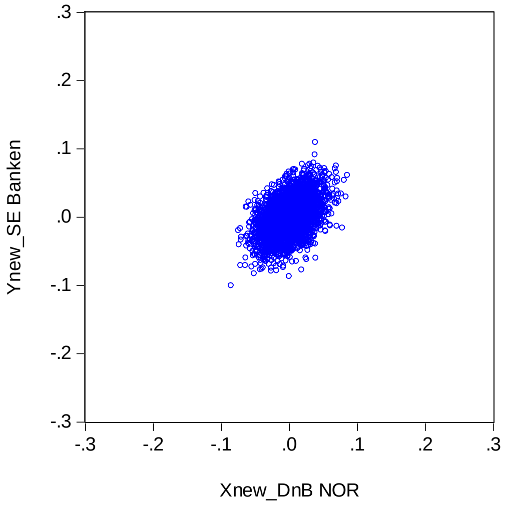


Figure 6 – Scatter plot of return data – student-t distributed, 1997-2010

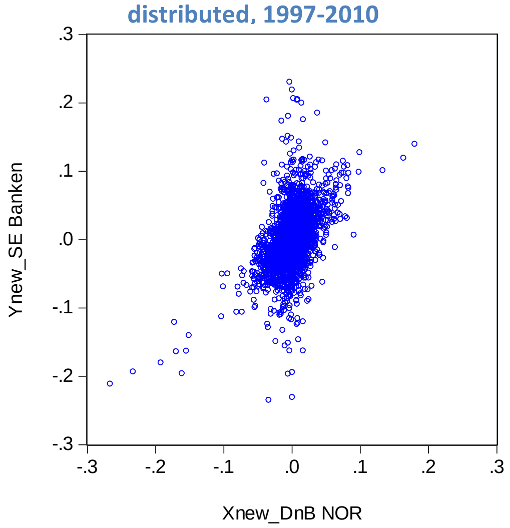


Figure 5 above shows the plots of randomly generated returns of a bivariate normal distribution. To do this I used the mean, standard deviation and correlation of the original pair of companies. In contrast to the fat-tailed distribution picture in Figure 4, the bivariate normal distributed returns do not exhibit many outliers, most observations are at the centre of the distribution, and the outliers we see do not, as in Figure 4, line up along a diagonal line. I interpret this to mean that for bivariate normal distributions, dependency at the tails vanishes. Figure 6 shows the plots for the random generated student-t distributed variables. Also for this exercise I used means, standard deviations and correlation coefficient of underlying pair of raw return data. The student-t distributed variables, exhibit more outliers than the normal distribution does and behave more like the raw data. The study by Schoenmaker et al. (2005) rightly concludes that the dependency at the tails, as observed in Figure 4, are signs of systemic risk. More details of how the bivariate normal distributed variables were generated, see the empirical appendix section 8.3.

4.2.3 Reduced-form approach: risk factors and dependencies

In the introduction of this thesis I listed some of the economic reasons why it is reasonable to assume that banks and insurers share risk factors. The resulting common exposures make returns of financial institutions co-move. In Schoenmaker et al. (2005) the authors develop a reduced-form approach to illustrate how these common risk factors affect dependencies between entities at the extreme ends of return distributions within and across the insurance and banking sectors. The systemic risk measure elaborated in the previous section is then added to the factor rationale to arrive at an actual value for the probability of a joint crash within and across sectors.

It assumed there is a macroeconomic risk factor (F) that all companies regardless of sector are exposed to, two sector-specific risk factors (A for insurers and B for banks) and firm specific risk factors (Y_i for banks and Z_j for insurers). Returns are denominated as G_i for banks and H_j for insurers, with $G_i = F + B + Y_i$ and $H_j = F + A + Z_j$ and that each of the risk factors are assumed to have distributions which are fat at the tails. The distribution at the tails will thus have a power-shape (as their tail distribution follows a Pareto distribution). In addition the marginal probabilities of a factor being above a threshold level t is:

$$P(A > t) = P(B > t) + P(F > t) = P(Y_i > t) = P\big(Z_j > t\big) = t^{-\alpha} \tag{7}$$

Figure 7 below shows two banks' portfolio lines $(F + B + Y_1)$ and $(F + B + Y_2)$. When searching for the probability that the returns of two banks exceed a threshold t at the same time is (or the probability of joint failure within a sector):

$$P(G_1 > t, G_2 > t) = P(F + B + Y_1 > t, F + B + Y_2 > t)$$

Figure 7 below shows that this condition only holds when we look along the green area of the $F + B$ axis. It is here were both portfolios are simultaneously above the threshold t. Therefore, the probability of joint failure is entirely driven by the common part of the axis. The red areas along the Y_1 and Y_2 axis do not satisfy the joint failure probability condition as at any of these regions both portfolios cannot be above threshold t at one and the same time. The same logic can be applied to a pair of insurers' portfolios. It is therefore possible to restate the probability of joint failure within a sector as:

$$P(G_1 > t, G_2 > t) = P(F + B + Y_1 > t, F + B + Y_2 > t) = P(F + B > t)$$

And using Feller's theorem which says that for very large threshold level t, in other words when very far out in the tail of a distribution, the probability of the sum of risk factors converges to the sum of the marginal probabilities. Meaning that the joint probability of failure within a sector is equal to[10]:

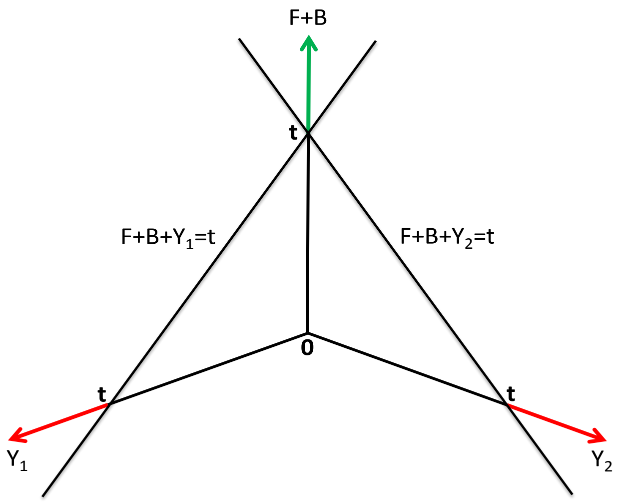
$$P(G_1 > t, G_2 > t) = P(F + B + Y_1 > t, F + B + Y_2 > t) = P(F + B > t) = 2t^{-\alpha} \tag{8}$$

Similarly, the risk that a bank i's portfolio would be above a certain threshold t, given that the threshold is sufficiently large and using Feller's theorem, is:

$$P(G_i > t) = P(F + B + Y_i > t) = 3t^{-\alpha} \tag{9}$$

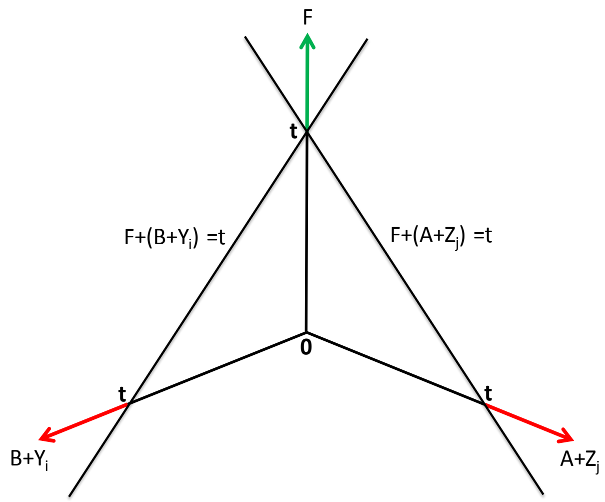
[10] The joint probability of failure for two insurers is written as:
$P(H_1 > t, H_2 > t) = P(F + A + Z_1 > t, F + A + Z_2 > t) = P(F + A > t) = 2t^{-\alpha}$

Figure 7 – Within-sector dependence



Source: de Vries (2008), Figure 2, p.5.

Figure 8 – Cross-sector dependence



Source: de Vries (2008), Figure 3, p. 6.

The same logic is used to derive the probability of joint failure across sectors. The two portfolios are then $(F + B + Y_i)$ and $(F + A + Z_j)$ for bank i and insurer j respectively. Here the condition

$$P\left(G_i > t, H_j > t\right) = P\left(F + B + Y_i > t, F + A + Z_j > t\right)$$

holds where the portfolio lines cross. That is the green area of the F axis on Figure 8 above. Again, the red areas of axis $F + Y_i$ and $A + Z_j$ do not allow for the above condition to hold as on those areas it is impossible for both portfolios to be above the threshold t simultaneously. The cross-sector joint failure probability can therefore be expressed as:

$$P\left(G_i > t, H_j > t\right) = P\left(F + B + Y_i > t, F + A + Z_j > t\right) = P(F > t) = t^{-\alpha} \qquad (10)$$

4.2.4 Theoretical value of downside dependence

Having presented the reduced-form approach to illustrate downside dependence within and across sectors the authors then use these probabilities and the systemic risk measure, equation (4), to compute a theoretical value for the downside dependence within and across sectors. The denominator of equation (4) can also be written as follows (for illustrative purposes see Figure 3):

$$1 - P(A \le t, B \le t) = P(A > t) + P(B > t) - P(A > t, B > t) \qquad (11)$$

and using equations (7) for the marginal probabilities, equation (5) for within sector joint probability of failure and equation (11), above, for the probability that one or more entities of the same sector fails, they arrive at the theoretical value for within sector systemic risk:

$$SR(k) = \lim_{t\to\infty} = \frac{P(G_1 > t) + P(G_2 > t)}{1 - P(G_1 \le t, G_2 \le t)} = \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - 2t^{-\alpha}} = \frac{6}{4} \qquad (12)$$

They do the same exercise for the cross sector systemic risk where instead of equation (9) they use equation (10) with the result:

$$SR(k) = \lim_{t\to\infty} = \frac{P(G_i > t) + P(H_j > t)}{1 - P\left(G_i \le t, H_j \le t\right)} = \frac{3t^{-\alpha} + 3t^{-\alpha}}{3t^{-\alpha} + 3t^{-\alpha} - t^{-\alpha}} = \frac{6}{5} \tag{13}$$

Therefore the theoretical value for within sector systemic risk is larger than that of cross sector systemic risk. A result that is quite logical since it was shown in the previous section that, within sector, entities simply share exposure to a higher number of risk factors than across sectors. In the article's empirical section the authors test whether this is the case.

4.2.5 Count measure for systemic risk

To be able to carry out tests on systemic risk, the authors first develop a count measure for systemic risk equation (4). As soon as one of the two entities reaches the threshold t, then the condition of one or more entity failing is fulfilled and this has probability $1 - P(A \le t, B \le t)$. The first one to arrive at t is the maximum of the two. It can therefore be stated that $1 - P(A \le t, B \le t) = P(max[A, B] > t)$, a univariate probability. When rearranged:

$$P(A \le t, B \le t) \quad = 1 - P(max[A, B] > t) \tag{14}$$

Then, the equality of equation (11) is rearranged and combined with equation (14):

$$\begin{aligned}
1 - P(A \le t, B \le t) &= P(A > t) + P(B > t) - P(A > t, B > t) \\
P(A > t) + P(B > t) &= 1 - P(A \le t, B \le t) + P(A > t, B > t) \\
P(A > t) + P(B > t) &= P(max[A, B] > t) + P(min[A, B] > t)
\end{aligned}$$

The term, $P(A > t, B > t)$, states the probability that both entities are above the threshold t at the same time. When the minimum of the two entities passes the chosen t, then and only then, this condition holds. Hence $P(A > t, B > t) = P(min[A, B] > t)$, another univariate probability. Equation (4) can therefore be expressed as two univariate probabilities:

$$\begin{aligned}
E[k|k \ge 1] &= \frac{P(A > t) + P(B > t)}{1 - P(A \le t, B \le t)} = \frac{P(A > t) + P(B > t)}{1 - P(A \le t, B \le t)} \\
&= \frac{P(max[A, B] > t) + P(min[A, B] > t)}{1 - 1 + P(max[A, B] > t)} = 1 + \frac{P(min[A, B] > t)}{P(max[A, B] > t)}
\end{aligned} \tag{15}$$

Estimating the two univariate probabilities in equation (15) above can be done by means of counting the number of observations above the threshold for the minimum and the maximum of A and B.

$$\widehat{SR(k)} = 1 + \frac{\#(min[A, B] > t)}{\#(max[A, B] > t)} \tag{16}$$

When using such count measure to estimate the probability of an exceedance over threshold t, we get an approximation to the actual probability. The reason is that the available return observations not necessarily exactly match the threshold. Hence the reported probability using the count measure will be an approximation of the theoretical continuous distribution.

4.2.6 Count measure for systemic risk, weighted

The systemic risk measure above represents systemic risk for asset returns that exhibit a on a one-to-one relationship. The data presented in the Schoenmaker et al. (2005) article does display equally weighted relationship. In contrast, the data used in this thesis behaves differently especially for the periods 1987-1996 and 1992-2003 sample periods.[11] In those time periods it is clear the relationship is not always equally weighted. For the time period 1987-1996, a possible explanation could be the quality of the data. In the empirical appendix on section 8.1, I mention some points of concern with regards to the quality of the data obtained predominantly from Datastream. An important reason for concern was the fact that, often, it is possible to observe constant prices over long periods of time. Sometimes I have been able to find reasons for these 'deviations', for example the half-year that the stock of insurer Storebrand was unlisted for reorganization and performance improvement reasons. In the end the data used in this thesis is the return index (RI) but even this measure depends on prices, so that constant prices will also create problems when generating ln returns series for the study. The effect of constant prices manifests itself as star-shaped scatter plots of ln returns with many plots along the axis. For an example, see figures 9 and 10 below.

Figure 9 – Scatter plot of returns, raw data 1987-1996

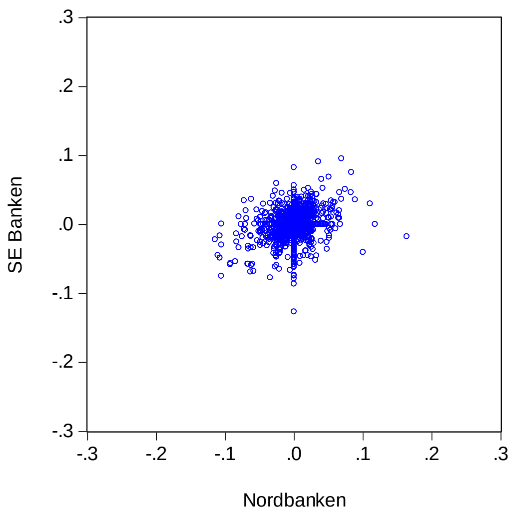
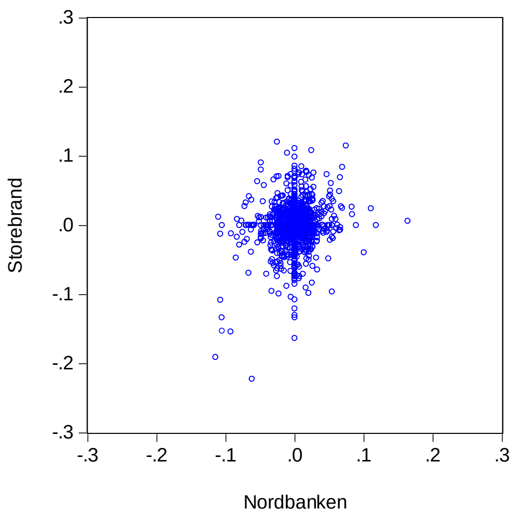


Figure 10 – Scatter plot of returns, raw data 1987-1996



In any case, I went through the data, looked for actual reasons for overly-extreme returns and long time periods of price stagnation, and corrected data where necessary (see section 8.1 for further details). After this exercise I was still left with not-equally weighted relationships so I decided to adapt the systemic risk measure to reflect the underlying relationship of the raw data. Equation (16) above is therefore expressed as equation (17) below and where c is the scaling coefficient obtained by OLS regressions.

$$\widehat{SR(k)} = 1 + \frac{\#(min[cA, B] > t)}{\#(max[cA, B] > t)} \tag{17}$$

Results of this estimate will be presented in section 6 where I rearrange equation (17) and express systemic risk as:

[11] For all scatter plots see the Eviews workfile (YYYY-YYYY.wf1, where YYYY stand for year) for each observation period, under the *raw-data* workfile page and objects *scatters_banks* and *scatters_ins*. In these workfiles banks and insurers are referred to as listed on Table 9 and Table 10 of the empirical appendix.

$$\widehat{SR(k)} - 1 = \frac{\#(min[cA, B] > t)}{\#(max[cA, B] > t)}$$

But before the results are presented, section 5 will discuss the two financial crises covered by the observation period of this thesis.

5 Financial crises in Scandinavia

Now that the theoretical definition of downside dependence within and across sectors and the both the univariate and the multivariate estimators have all been presented, I will now discuss the Scandinavian setting before introducing the empirical analysis on section 6. This provides the reader with the necessary context. The time period of study encompasses two financial crises, one in the 1990s and the second one, the entire world is yet to exit from. Therefore, this section will provide a brief account of each of these two crises as experienced in Scandinavia.

5.1 The 1990s financial crisis

In order to study the 1990s financial crisis we need to go back to the 1980s, when key events unfolded that collectively contributed to the ensuing of the financial crisis. Interestingly, the financial crisis unfolded more or less simultaneously across the Scandinavian countries, which, at first glance, may be interpreted as a sign of contagion and of high levels of systemic risk.

Running up the first half of the 1980s the Scandinavian financial markets were characterized by stringent regulation that resulted in financial markets that were quite isolated (Fossli and Burton, 1991 and Taylor, 1999). Although at the time, the rest of Europe also had a rather domestically focused financial markets. Restrictions in Sweden ranged from restriction on currency flows, restrictions on bank lending rates, credit ceilings, placement quotas for insurance companies and barriers to entry of foreign players (Östman, 2009). In Norway, restrictions were similar to those in Sweden with interest rates set below market rates and limits on capital flows and lending (Wilse, 2004). Restrictions in Finland were similar to those in Norway and Sweden and included restrictions on deposit rates thus assuring lack of price competition (Drees and Pazarbaşiouğlu, 1995). These restrictive measures were all designed to give governments power to steer their home economy in the direction of their macroeconomic policies, to make sure banks' profits remained stable and thus guaranteeing financial stability. The financial market was not driven by market forces and lacked competition. As a result of stable financial markets, capital requirements were minimal or not always enforced. Finally it should be mentioned that Denmark shared the same rigid regulatory system as the other Scandinavian countries but in contrast, begun deregulating already in 1980, some 5 years prior to the rest (Vastrup, 2009).

Market pressures made themselves felt with the dawn of money markets and grey markets begun to emerge to bypass the strict regulated banking scene. As a response to this and to the looming single European market, deregulation gathered pace as the 1980s progressed. It was hoped that deregulation would put the banks in a better position to compete in a more international financial market. The result was a surge in lending due to an increase in demand and also as a defence strategy by banks to fend off competition. The surge in lending for real estate acquisition and development purposes was particularly acute because of the introduction of tax deductions for property-linked debt. In turn, this drove property prices upwards. Banks not used to a liberalized market failed to carry out proper risk assessments which resulted in increased risk taking. In addition, banks responded to competition by carrying out a string of mergers in an attempt to secure growth (Drees and Pazarbaşiouğlu, 1995).

Then 1986-1987 saw the Nordic economies overheat. Adequate economic policy was lacking and the overheating was not dealt with. In this climate, Norway was the first country to hit the rocks. In 1986 oil prices collapsed sending the country into a deep recession. Property prices collapsed and losses from property investment began to emerge (Taylor, 1999). By 1989 falling property prices claimed their first victim in Norway, Norion Bank. In Sweden and Finland also entered a deep recession although a few years later. Finland was facing the effects of increased interest rates following German unification and loss of exports as a result of the collapse of the Soviet Union. Nevertheless the symptoms across the countries were the same and many banks were either made to merge or taken over by the authorities (Honkapohja, 2009 and Fossli and Burton, 1991). Denmark and the rest of Europe too experienced a recession in the years 1992-1993. Despite suffering large loan losses during the crisis, Danish financial institutions came out of the crisis in a better state as they had started reorganizing themselves sooner. Danish regulations demanded capital ratios beyond those stipulated by the Basle I accord which was to be implemented in 1991. Hence, in Denmark, loan loss provisions were larger than necessary initially. In 1990-1992, Danish banks were better capitalized than the ones in other Nordic countries. Because the latter came from an environment of financial stability and because the Danish had had more time to adapt to a deregulated business environment, other Nordic banks were not sufficiently capitalized when loan losses begun to mount (Vastrup, 2009).

The total cost of the interventions across the countries were met primarily by the state, but in Norway also by the banking industry. Table 1 below summarizes total loan losses and cost to the public incurred during this financial crisis. Following years of reorganization banks were gradually put back into private hands and their stocks were listed once more. Insurance companies recovered from losses made in their reinsurance activities. Authorities have, since the crisis, managed to recuperate expenses due to rescue measures and, in some cases, even made a healthy profit.

Table 1 – Losses, loss provisions and public support for commercial banks in the Nordic countries, 1991-1993

	Losses and loss provisions 1991–93				Public support 1991–93[1]	
	In billions, national currency units	In per cent of lending	In per cent of GDP	In per cent of balances	In billions, national currency units	In per cent of GDP
Denmark[2]	44.5	9.1	5.2	4.5	3.9	0.4
Sweden	151.6	17.9	10.5	10.1	65.0	4.1
Norway	39.2	8.4	5.6	6.6	25.0	3.6
Finland	46.4	13.1	9.8	6.2	38.6	8.1

Notes: Accumulated figures.
(1) Actual support paid out; for Sweden and Denmark until end of September 1994, for Denmark repayments excluded.
(2) Excluding the Faroe Islands.

Source: Danish Ministy of Economic Affairs (1994) quoted as Table 8.1 in Vastrup, 2009, p. 251.

5.2 Today's financial crisis

Having recovered from the losses made during the financial crisis of the 1990s, nationalized banks were put back into private hands. [12] The realization of an integrated European financial market and the pressures imposed by a the single European monetary union drove banks to seek to reassert their position at home and abroad. Therefore a wave of consolidation begun yet again 1995 with the merger of the two Finnish banks KOP Bank and Suomen Yhdyspankki to form Merita. In 1997 Merita merged with the Swedish Nordbanken to form MeritaNordbanken. 2000 saw the birth of the giant pan-Nordic bank Nordea. Itself the result of a takeover by MeritaNordbanken of the Danish bank Unidanmark and the Norwegian bank Christiania Bank. In 1999 the Norwegian Fokus Bank was taken over by the Danish Danske Bank. Over in Norway, in 2000, DnB NOR was formed following the acquisition of Nordlandsbanken by Den norske Bank. The insurance sector also had its share of mergers and joint-ventures.

Next the banks looked to the independent new states of Lithuania, Latvia and Estonia. They bought up local banks and managed to establish themselves as the market leaders in those countries. Today, Swedbank and Nordea are the two largest banks in the Baltic. Unfortunately for the Nordic banks, the onset of the current financial crisis in 2007 drove the Baltic countries into a recession and loan losses from activities in the region begun to mount for the Nordic banks (Ward, 2010). But the recession also occurred in Russia, Poland and the Ukraine, where the Scandinavian banks also ventured into in the years 2005-2006, further deepening loan losses.

During 2008 Scandinavian banks faced other headaches of the financial crisis in the form of liquidity shortage and other asset write downs. Governments and central banks stepped in to help out the banks. The Swedish government and Central Bank rolled out a string of measures to ensure liquidity

[12] The governments of Norway and Sweden still have large stakes in DnB NOR (former Den norske Bank) and Nordea (former Nordbanken) respectively.

to the banks. All countries in the region have issued guarantee programmes like the Swedish in which, against a fee, the state agreed to guarantee payments in case of default by a bank (Finansinspektionen, 2010). As in the rest of Europe, Nordic central banks have all reduced key policy interest rates and kept them low until today. The Swedish, Danish and Norwegian central banks have provided banks with long maturity loans. Despite these well coordinated efforts bank failures did occur. In August 2008, Denmark's central bank had to acquire Roskilde Bank, the 8th largest bank in the country at the time and a string of other smaller banks in the country (Danmarks Nationalbank, 2009). The other countries have not experienced any nationalization of their banks.

Currently, the economic outlook of the Baltic countries looks more stable and governments in that region have taken significant measures to stabilize their public finances. Hence, the banks are expecting to see a reduction in the amounts of loan losses. Central banks and governments have started to wind down their support measures. Even the solvency crisis of Greece has not hurt the banks' balance sheets too badly and the region has not seen a sovereign debt crisis of the type we now see in the parts of the world. Recovery of banks is therefore set to be on a stable course in Scandinavia.

6 Empirical results

In this section, results for both the univariate risk, equation (3) and multivariate systemic risk, equation (17) estimators. I will start by presenting the data and then move on to interpret the results starting with the univariate ones and following up with the multivariate ones.

6.1 Data

The data sample consisted of the largest banks in terms of market capitalization and on interesting characteristics. Events such as failure or government support were considered to be such interesting characteristics. In the end, I had collected, primarily, from Datastream daily return index data for 5 banks and 5 insurers for any one time period. For the multivariate model, this resulted in 10 possible combinations for the two within sector samples and 25 combinations for the cross sector sample. The observation periods, were:

Actual time period:	Referred to as:
1 January 1987 to 31 December 1996	1987-1996
1 January 1997 to 19 April 2010	1997-2010
1 January 1992 to 31 December 2003	1992-2003

For more comprehensive details of the data selection process, please consult the empirical appendix on section 8.1.

6.2 Univariate results

Table 2 below depicts the estimated probabilities for a threshold loss of -15% in a day. For the 1992-2003 and 1997-2010 samples the average probability of returns exceeding that threshold are smaller for banks than insurers. In the 1987-1996 sample, banks were more likely than insurers to exceed the threshold level. With banks having a 0.422% and insurers 0.164% probability of losing 15% or more of the value of their stock in a single day. For banks, this means that once every (1/0.00422)

237 days or approximately one day per year. For insurers, this means once every (1/0.00164) 610 days or one day per approximately 2 years.[13]

In 1987-1996 banks were perhaps seen as more risky by the market because running up to government intervention during the peak of the 1990s' financial crisis, market participants simply could not accurately anticipate what the government would do. For the later time periods, government intervention was a fact and thus a precedent of support measures was established. Contrary to banks, insurers had not been at the receiving end of government support. Therefore, for the later time periods, it is possible to assume that the markets perceived insurers to be more risky than banks on average. The price of bank and insurance stocks would reflect this sentiment and, in a stress situation, the share price of insurers could possibly drop further than that of a (large) bank. I find some level of support to this claim by looking at the average minimum returns observed for insurers and bank in each of the three sample periods. In 1987-1996, the average minimum returns for insurers was lower than that of banks at -18.8% against the banks' -27.8%. In the later sample periods this pattern is reversed and insurers have a higher average minimum returns than banks. For the 1992-2003 sample, the average minimum returns observed among insurers was -27.3% and for banks this was -25.2%. In 1997-2010 these figures were -19.3% and -18.6%. However, this line of reasoning is not supported by the average skewness observed in each sample. In 1987-1996, returns of insurers were more negatively skewed than those of banks. Suggesting insurers were more likely to display negative returns than banks and we could expect the loss probability to be higher for insurers than for banks which is not the case. In 1992-2003 insurers' returns were less negatively skewed than those of banks and we could expect the loss probability to be lower for insurers than for bank which is not the case. Skewness of returns during 1997-2010 is on average insurers' returns were more positively skewed than those of banks and, as was the case for the 1992-2003 sample, we would expect a lower loss probability for insurers than for banks which, again, is not the case (for summary statistics see section 8.2.1 on empirical appendix). Nevertheless, the results reported here for the 1992-2003 sample period, are in line with those observed with those observed by Schoenmaker et al. (2005).

Of the individual results for the sample period 1987-1996, the highest is the one for Den norske Bank with a probability of a loss of more than 15% in any given day being 1.389%. In other words, between 1987-1996, this meant once every (1/0.01389) 72 days. In fact, we can view the bank as having ceased its operations had it not been for state intervention at the peak of the 1990s' financial crisis. In 1997-2010 the highest observed loss probability is that of the Norwegian insurer Storebrand. This could be explained by the large drops in share price experienced by the company. During the entire observation period, the line plots of the returns of the company's stock show large drops in the second half of 2001, in the mid of 2002 and in the end of 2008. Following the attacks on the World Trade Centre in September 2001, financial markets were left in turmoil. This was particularly acute for insurance and reinsurance businesses. Prior to the attacks, the Finnish insurer Sampo had launched a bid for Storebrand but as the Storebrand share begun to drop in value after the attacks, Sampo withdrew its offer deeming it excessive in view of the market value development

[13] With one year being defined as 260 days.

of Storebrand (Brown-Humes et al., 2001).[14] In May 2001, Storebrand's stock dropped sharply again following accusations by Den norske Bank of hiding loan losses of Finansbanken, a banking unit of Storebrand. Den norske Bank, was at the time engaged in a due diligence process of Storebrand. Eventually, the merger did not go ahead despite Storebrand having been cleared of any wrongdoing by independent auditors (Criscione, 2002). The last of the large share value drops by Storebrand was in October 2008, following the collapse of the Icelandic banks. In an attempt to maintain liquidity, parties with large exposure in the Icelandic banks begun to sell off some of their assets. The investment company Exista had a 25% stake in the Icelandic bank Kaupthing. After Exista sold off its 20% stake in the Finnish insurer Sampo, financial markets feared the company would follow up by selling its stake in Storebrand. As a result the share price of Storebrand dropped significantly (Anderson, 2008). This list of large negative returns by Storebrand is confirmed by the summary statistics (see section 8.2.1 of the empirical appendix), where we can see that of all insurers, Storebrand's return distribution is the only one among the insurers that displays negative skewness. Across the samples, the magnitudes of probabilities observed are larger than those in the study by Schoenmaker et al. (2005).

[14] On the 1st of October 2001, the Storebrand share had dropped an impressive 19.6% on the previous day.

Table 2 – Loss probabilities($x_{var} = -15\%$) and Hill estimators of real data and all samples

Sample	Company name	Tail index estimate, $\hat{\alpha}$	Probability, $\hat{p}$	Sector $\hat{p}$ averages
1987-1996				
	Christiania Bank	2.65756	0.00219	
	Danske Bank	2.75681	0.00013	
	Den norske Bank	1.43387	0.01389	
	Nordbanken	2.05930	0.00253	
	SE-Banken	2.25630	0.00235	**0.00422**
	Codan	2.57520	0.00044	
	Hafnia Holding	1.78170	0.00298	
	Sampo Group	2.31708	0.00225	
	Skandia	2.85600	0.00080	
	Storebrand	2.68961	0.00171	**0.00164**
1997-2010				
	Danske Bank	2.88648	0.00056	
	DnB NOR	2.57414	0.00120	
	Nordea	3.00066	0.00068	
	Swedbank	2.75741	0.00121	
	SE-Banken	2.62706	0.00144	**0.00102**
	Alm Brand	2.84277	0.00076	
	Codan	2.77062	0.00030	
	Sampo Group	2.91732	0.00071	
	Skandia	3.17297	0.00185	
	Storebrand	2.39260	0.00219	**0.00116**
1992-2003				
	Danske Bank	3.26551	0.00019	
	DnB NOR	2.40534	0.00096	
	Nordea	2.79118	0.00096	
	Swedbank	3.51989	0.00019	
	SE-Banken	2.35158	0.00224	**0.00091**
	Alm Brand	2.40525	0.00342	
	Codan	2.98257	0.00030	
	Sampo Group	3.15452	0.00088	
	Skandia	3.20773	0.00160	
	Storebrand	2.56399	0.00116	**0.00147**

For all coefficients included in the calculation of $\hat{p}$, see Table 14 in the empirical appendix.

6.3 Multivariate results

In this section, I present only the average results for each sample period. Full pair-wise results are reported in the empirical appendix on section 8.5 and tables 15 to 32. For the interpretation of this section, interesting individual values from these tables are used. The actual threshold value of 3.6% was chosen as it was a suitable value for all those pairs of stocks, across the samples, for which their plots of $\widehat{SR(k)} - 1$ vs. higher order statistics showed evidence of systemic risk at the tails.[15] In

[15] The higher order statistics represent the threshold series ordered in descending order.

section 8.4 of the empirical appendix I explain in more detail how I arrived at the selected threshold point. In addition, as dead stocks are included in the samples, I do not always have the same number of observations for each of the stocks (for individual sample size see Table 14 on section 8.5.1 of the empirical appendix). Therefore, in this multivariate systemic risk exercise I use sample sizes that include data where the two entities' return data overlap. Tables 15 to 32 report the resulting pair-wise sample sizes.

6.3.1 1987-1996 estimation

The first sample period, as was mentioned earlier, coincides with the financial crisis that took place in Scandinavia in the early 1990s. At first, it might be surprising that, for the real data, the average systemic risk estimates reported in Table 3 a) are so low. For between banks, the probability that one bank crashes given that one has already done so is 1.73%, for between insurers this probability is non-existent and for between sectors it is 0.96% . Bearing in mind the financial crisis in Scandinavia happened more or less simultaneous in the different countries it would seem, at first sight, fair to expect higher values for this sample period. Line graphs of returns confirm the expectation that systemic risk readings should be higher than now observed. Figure 11 below depicts a line graph where the returns for Den norske Bank and SE Banken have been laid out for the time period in which both companies exist. It is possible to see that, on various occasions, these two stocks experience extreme movements in their returns around the same time. Also, where the movement is not simultaneous, an evident lag is visible suggesting an extreme return is observed one day for one stock and that of the other reacts with a time delay.

Figure 11 – Line graphs of ln returns, Den norske Bank and SE Banken, 1987-1992

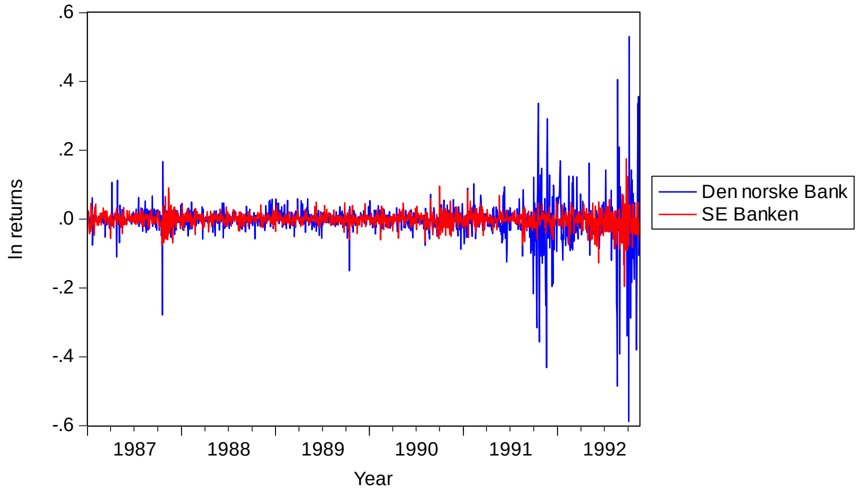
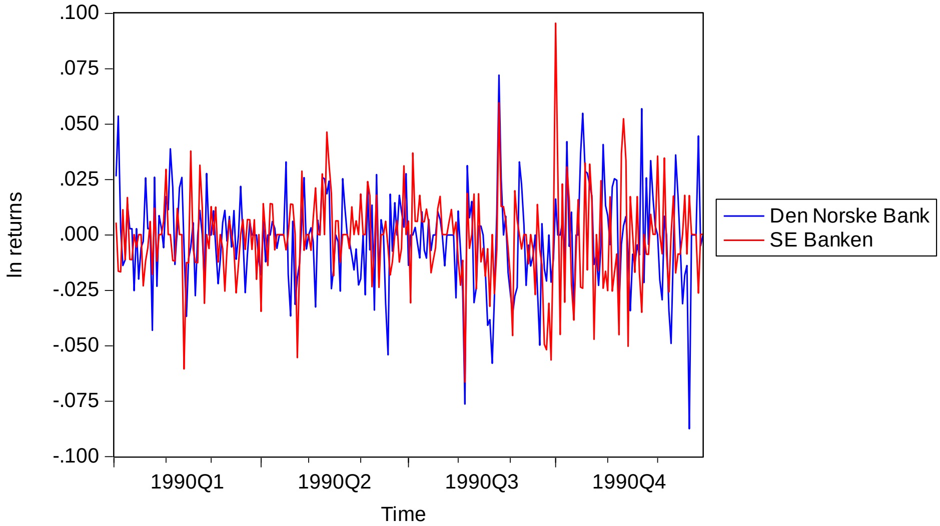


Figure 12 below depicts the same stocks but now for a smaller time window. One example of the 'lag' effect is seen on the 13th of February 1990 when SE Banken has a daily return of approximately -6% and, one day later, Den norske Bank has a daily return of approximately -4%. As an example of simultaneous adverse moves it is possible to see that on the 6th of August 1990, Den norske Bank reported a daily return of around -8% and SE Banken of approximately -7%. Hence, there is evidence that suggests more systemic risk should be observed than what is now the case. Possibly, this level of systemic risk could be captured if instead of using contemporaneous return observations when measuring systemic risk, both contemporaneous and lags of returns were used. This exercise though is beyond the scope of the current thesis but could be explored in potential follow-up papers.

Figure 12 – Line graphs of ln returns, Den norske Bank and SE Banken, 1987-1992



Another potential explanation for not observing the anticipated systemic risk level is the quality of the data. In the empirical appendix on section 8.1 I bring up issues encountered when examining the raw data. The most striking of them being long time periods of price data stagnation. This causes scatter plots of company pairs' returns to exhibit many plots on both x and y axis. Meaning that there could be instances where entity A exhibits an extreme return but entity B does not, because of price stagnation. This might induce one to think there is no relationship between the variables at the extremes. Price stagnation could in those instance masque a possible relationship, one in which the location of the dot on the scatter plot would be on any of the quadrants.[16]

Table 3 – 1987-1996 Estimation results, $\widehat{SR(k)} - 1$ and t = 0.036

a) Real data

	Mean	
	Bank	Insurer
Bank	0.0173	0.0096
Insurer	0.0096	0.0000

b) Bivariate normal data

	Mean	
	Bank	Insurer
Bank	0.0019	0.0003
Insurer	0.0003	0.0000

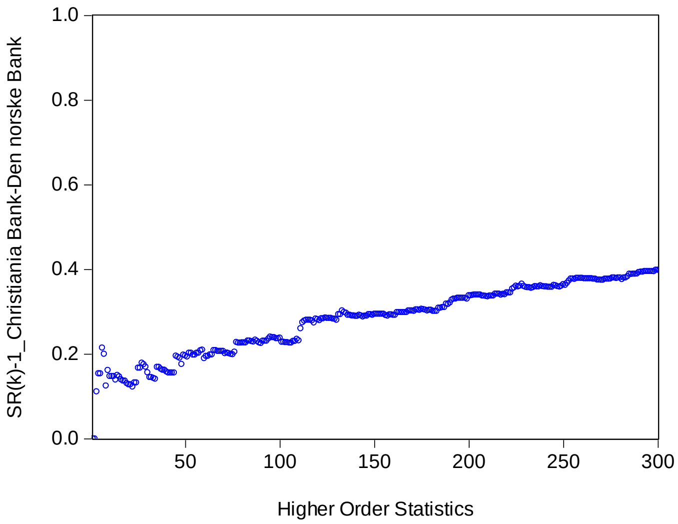
Of the individual pair results shown on Table 15, the result for Christiania Bank-Den norske Bank is the highest at 15.63%. These two banks are referred to as bank 1 and 3 on the pair-wise correlation matrix on Table 12 of the empirical appendix. From Table 12 we see that the correlation between these two banks was 0.5418. If the correlation coefficient is taken to be a measure of dependency, the correlation coefficient for this pair of stocks suggests a higher dependency between the two banks than what is observed at the tail of the return distribution and measured by equation 17. As was mentioned earlier in the literature review on section 2, the correlation coefficient is based on the assumption of normality which was shown in section 3 not to be the case in this study. Section 2 also brought up that the correlation coefficient is mainly driven by observations in the middle of the distribution. This can be interpreted to mean that dependency is high in the middle of a distribution, as measured by the correlation coefficient, and diminishes but not vanishes towards the tail of it, as

[16] If in quadrants I and III, the dependency is positive and if in quadrants II or IV dependency is negative.

measured by the systemic risk measure. This particular example illustrates that for extreme events, the correlation coefficient as a measure of dependency overestimates that dependency and is not a suitable measure for tail dependency.

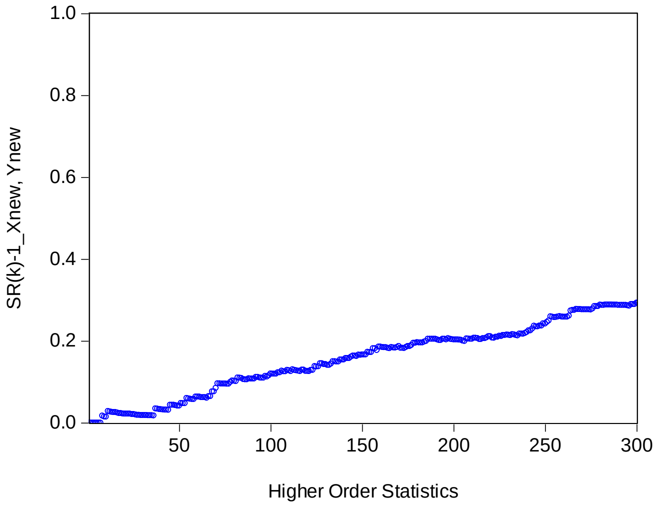
Figure 13 below shows the plot for $\widehat{SR(k)} - 1$ vs. higher order statistics for the bank pair. The plot shows the usual behaviour of student-t distributed variables. Where for the first higher order statistics the systemic risk measure is unstable and then it quickly stabilize around rank 90. The systemic risk reading for the threshold of 3.6% is done at rank 30.

Figure 13 – $\widehat{SR(k)} - 1$, Christiania Bank-Den norske Bank, 1987-1996, real data*



* Total number of observations 1246.

Figure 14 - $\widehat{SR(k)} - 1$, Christiania Bank- Den norske Bank, 1987-1996, bivariate normal data*



* Total number of observations 1246.

To be able to explain the high levels of systemic risk for this pair of entities, one must go back to the history of Den norske Bank and seek any possible factors that could explain this. In the mid-1980s the banking sector in Scandinavia experienced many mergers. As deregulation became a fact, the up-to-then heavily regulated and isolated banking market decided to expand by means of mergers. Amalgamation, it was believed, would have the benefit of enhancing competitiveness of banks in a looming single European market. Den norske Bank was formed in 1990 following a merger between Den norske Creditbank and Bergensbanken.[17] The two banks were already not doing well when the merger took place. At the time of the crisis both Christiania Bank and Den norske Bank were taken over by the state. Perhaps the market had already perceived both banks as risky running up the nationalization and that therefore we would see this reflected in their high systemic risk estimate. The banks are also the only two Norwegian banks in the sample. Exposure to a common domestic market could also be driving their systemic risk measure up. In the 1987-1996 sample, although systemic risk measures observed across the sample are altogether low, systemic risk is higher nationally than across borders.[18] An outcome which reminds of the one found in the Hartmann et al. (2005) article discussed earlier.

When calculating the estimates for systemic risk using the bivariate normal data, the values as anticipated, are lower than those observed for the real data as shown in Table 4 b) above. This is in line with the reasoning discussed earlier in section 4.2.2. We see this difference by comparing figures 13 and 14 above. Figure 14 depicts the bivariate normal data and it is possible to see that at the tail of the distribution systemic risk is zero and only gradually increases towards the centre of the distribution. The fact that at rank 300 the raw data show higher systemic risk than the bivariate normal data, could be due to the centre of the distribution, where systemic risk should be higher for bivariate normal data than for student-t distributed one, is located beyond the 300 rank.

With respect to the theoretical systemic risk difference to be expected between the within sector and cross sectors presented by Schoenmaker et al. (2005) and revisited in section 4.2.4 above, the real data of the 1987-1996 sample only partially supports it. Table 3 a) above showed systemic risk between banks is higher than across sectors. This supports the proposition that systemic risk within sector should be higher than across sectors. Estimates for within the insurance sector, on the other hand, do not render support for the proposition discussed in section 4.2.4. This deviation could possibly be put down to poor quality of the data used as discussed above and section 8.1 of the empirical appendix.

6.3.2 1997-2010 estimation

The second sample period covers a period in which Scandinavian financial institutions experienced many mergers and the effects of yet another financial crisis. Table 4 a) below shows systemic risk within the banking sector is higher than that across sectors over the period by a factor 10.

[17] The formation of the bank was indeed the result of the merger between Den norske Creditbank and Bergensbanken. Datastream has data for Den norske Bank from 1973 to 1991 when the bank was nationalized. The price data follows the same pattern as the one resulting from adding the market-capitalization-weighted price data of the bank's two underlying entities. This suggests the data for Den norske Bank prior the bank's formation, could be the result of such an exercise by the company running Datastream.

[18] See the systemic risk estimate for the cross sector Norwegian pair Christiania Bank-Storebrand. It is 6.58% (see Table 17 in the empirical appendix) and is the second highest value after Den norske Bank-Storebrand (7.44%). The third highest scoring cross sector result is the one for the Swedish pair SE Banken-Skandia (4.90%).

Table 4 - 1997-2010 Estimation results, $\widehat{SR(k)} - 1$, t = 0.036

a) Real data

	Mean	
	Bank	Insurer
Bank	0.1304	0.0150
Insurer	0.0150	0.0034

b) Bivariate normal data

	Mean	
	Bank	Insurer
Bank	0.0435	0.0028
Insurer	0.0028	0.0000

For insurers, the increase in systemic risk was not very impressive. For the insurance sector, on average, systemic risk was 0.34% during 1997-2010 whereas it was 0% in 1987-1996. The low value of systemic risk for insurers is confirmed by the patterns of the $\widehat{SR(k)} - 1$ vs. higher order statistics plots for insurer pairs. All these plots show barely any systemic risk at the tails of the return distributions. The banking sector shows a significant increase in systemic risk relative to those observed in the 1987-1996 sample. On average, systemic risk for banks was 13.04% in 1997-2010 and in 1987-1996 this figure was 1.73%. The increase in systemic risk is consistent with the findings of Hartmann et al. (2005). In their study, the banking sector was found to have been more exposed to systemic risk in 2004 than in the early 1990s. With systemic risk increasing significantly around mid-1996 in the case of the euro area and around the end of 1995 for the U.S.. In Scandinavia, there has not been a common currency as is the case for the euro countries. Therefore the increase in systemic risk among banks in the Nordic countries could be attributed to increased amalgamation of banks and common exposures like the witnessed aggressive expansion by many of the large Nordic banks to the Baltic countries at the end of the 1990s.

Within the banking sector, the SE Banken-DnB NOR (bank 5 and 3 respectively) combination shows the largest value of systemic risk for cross country bank pairs 10.71% (see Table 21 of the empirical appendix). The pair's correlation coefficient is 0.4673 (see Table 12). Again this particular example demonstrates the unsuitability of the correlation coefficient as a measure of dependency for extreme event as was discussed earlier for the case of Christiania Bank-Den norske Bank in the 1987-1996 period. The correlation coefficient overestimates dependency at the tails.

The systemic risk observed in the case of SE Banken-DnB NOR could be explained by the fact that both banks share one factor in common, of the Swedish banks in 2009, SE Banken came in second place when it comes to market share of lending in the Baltic countries (Sveriges Riksbank, 2009). Currently, DnB NOR also carries out significant part of its operations in the Baltic countries. SEB Baltic Holding and DnB NORD are the entities set up by both banks to coordinate operations in the Baltics. In 2009, half of DnB NOR's loan losses were from the region (Norges Bank, 2010). For Swedish banks, the Swedish Central Bank's estimates for after 2009 were that majority of loan losses would come from operations in the Baltic countries. Beyond exposure to the Baltic countries, both banks have activities in Poland and Russia. Common macroeconomic exposures as these could explain the high systemic risk observed for this pair of entities at least for the last three years or so. Furthermore, according to Thomson One Banker data, both banks have the Norwegian State as a major stakeholder which could be yet another source of common risk for the banks which could drive systemic risk upwards.

Of the average within sector systemic risk estimates reported on Table 22, the pair Skandia-Sampo shows a positive but very low (0.83%) dependency. This could possibly stem from the fact that in 1999, Sampo bought a 23.6% stake in the Finnish insurer Pohjola Oyj. With this move, Sampo also acquired the 10% stake which Pohjola Oyj held in the Swedish insurer Skandia. In turn, Skandia held a 10% stake in Pohjola Oyj. Furthermore, in 2001 Sampo together with another Finnish insurer were given permission to participate in the non-life insurance venture If Skadeförsäkring Holding AB. That venture had begun in 1999 and was controlled jointly by Skandia and Storebrand. All plots of $\widehat{SR(k)} - 1$ vs. higher order statistics for insurers are flat except for those of Skandia-Sampo and Skandia-Storebrand. Although the dependency levels observed are very low indeed (see also Table 22).

Across sectors, systemic risk is a very low 1.50%. This outcome was surprising as news reports for the years 1997-1998 in their aim to merge and grow to face looming competition, banks not only merged with other banks but they also merged with insurers in an aim to form '*bancassurance giants'* (Brown-Humes, 1997). Therefore, I expected to see higher systemic risk estimates across sectors than was the case. In the cross sector sample, the SE Banken-Sampo pair stands out. At a threshold level of 3.6%, the pairs systemic risk estimate is 5.11% (see Table 23 in the empirical appendix) is the highest one in the cross-sector sample. A possible explanation could be that SE Banken is reported to have had a 9.9% stake in Sampo back in 1998. From Sampo's own website we see that over the years 2005 to today, SE Banken's stake has been more than 15% on average.[19] In fact, of the Swedish banks, Nordea and SE Banken have been the largest shareholders in Sampo over the years 2005 to today. This could explain why, in this sample, I see large systemic risk readings for the combinations of Sampo with both these banks. Thus, the ownership positions here could be the common risk factor, F, driving systemic risk up. However, since Nordea has had a significantly higher stake in Sampo (more than 30% on average) than SE Banken (more than 15% on average) I would have expected the systemic risk reading for Nordea-Sampo (3.25%) to be higher than that of SE Banken-Sampo (5.11%). As this is not the case, there may be additional factors out there which, given stake levels, make SE Banken share more risk factors with Sampo than Nordea does. In addition, the fact that I see an increase in the systemic risk results of Nordea-Sampo and SE Banken-Sampo from 1987-1996 to the 1997-2010 sample (see Table 17 and Table 23 respectively) confirms the observed trend of banks merging to form giant bancassurance entities.[20] One last remark with respect to Nordea and SE Banken could be in place. The within sector systemic risk for their combination is the highest of all bank pairs at 31.65% in 1997-2010. Perhaps dependency is driven upwards simply because both are Swedish banks and both have such large stakes in Sampo. Altogether the systemic risk measures for the Swedish bank combinations and the possible cross-country combinations, suggest systemic risk for banks was larger nationally than across borders. Again, this is in line with the outcomes observed for euro country banks by Hartmann et al. (2005).

Finally, when comparing the systemic risk observed in the real data with that of the bivariate normal data, Table 4 above shows that on average systemic risk is lower for bivariate normal distributions (see Table 4 b)) than for distributions that behave like a student-t distribution like the real data (see Table 4 a)). Also, as in the previous sample, systemic risk is higher for the banking sector than across

[19] Sampo shareholder data obtained from: http://www.sampo.com/ir/shareholders

[20] In section 8.1.3 of the empirical appendix I explain that it is safe to view Nordea as the successor of Nordbanken even though Nordea was the result of merging the Swedish bank Nordea, the Finnish bank Merita, the Norwegian Christiania Bank and the Danish Unidanmark.

the sectors as was expected (see section 4.2.4). Although this is not the case for the insurance sector.

6.3.3 1992-2003 estimation

The last of the samples includes the same entities that were included in the 1997-2010 sample. Table 5 a) below reports the results which are somewhat lower than those observed in the article by Schoenmaker et al. (2005).[21] For Scandinavia, on average, systemic risk for the banking sector is 3.09% whereas the same figure for Europe, as presented in Schoenmaker et al. (2005), is 10.38%. Markedly lower thus. For the insurance sector, the figure for Scandinavia is 0.06% and for Europe 11.70%. In the Nordic countries systemic risk is higher in the banking than in the insurance sector. This is the opposite relation than that observed for Europe. The cross sectors systemic risk is 0.15% in Scandinavia and 7.44% in Europe. The European sample exhibited lower systemic risk across sectors than within sectors. In Scandinavia this is only true when comparing the cross sectors with the banking sector but not when comparing it with the insurance sector. What is somewhat puzzling about the results for the Nordic countries is that in the years 1997-1998, many mergers were observed. The early 2000s saw a wave of aggressive expansion by Scandinavian banks into the Baltic region. As a result it could be expected that the banks would have more common exposure and higher levels of systemic risk. For the insurance companies, I mentioned that Skandia, Storebrand and later Sampo were participants of the joint venture If and that insurance companies were known to hold large stakes in one another. Even for the insurance sector, more systemic risk would have been expected. With regards to systemic risk across sectors, the same analogy applies. Banks did aim not only to grow through mergers but they also aimed to be large bank-insurance houses. In addition, as banks crossed their national borders, they encountered a customer base that had fairly similar needs to the one at home. This cultural homogeneity in their cultural base could be seen as yet another common risk factor which should drive systemic risk up.

Table 5 – 1992-2003 Estimation results, $\widehat{SR(k)} - 1$, t = 0.036

a) Real data

	Mean	
	Bank	Insurer
Bank	0.0309	0.0015
Insurer	0.0011	0.0006

b) Bivariate normal data

	Mean	
	Bank	Insurer
Bank	0.0092	0.0029
Insurer	0.0029	0.0000

A possible explanation could be that by merging and venturing into new activities, financial institutions' main focus was to capture a large market share at home so that, in turn, they could be in a better position to fend off foreign competition. And that despite of what could be expected, given events, financial institutions between the years 1992-2003 had retained their insular character to some extent. We see from tables 3-5 that systemic risk within banks (insurers) increased stepwise through time, with 1.73% (0%) in 1987-1996, 3.09% (0.06%) in 1992-2003 and 13,04% (0.41%) in 1997-2010. Furthermore, the Baltic expansion activity was perhaps at its most aggressive after 2003 and therefore the systemic risk results would not be driven so much by the effect of this common exposure. Finally, the question of data reliability (see section 8.1) remains and would affect the outcomes.

[21] See tables 27-32 in section 8.5.2 of the empirical appendix for the full results of the banking, insurance and cross sectors.

As in the previous sample periods, in 1992-2003, systemic risk is lower for the banking sector than for the cross sectors. The opposite relation is true for the insurance sector and the cross sectors. Table 5 b) above, as did its equivalents in the previous samples, reaffirms the proposition of section 4.2.2 that, at the tails, systemic risk is higher for a student-t type of distribution than for a bivariate normal one.

6.3.4 On correlation and systemic risk results

Earlier in this section, for the samples 1987-1996 and 1997-2010, I offered a brief comparisons of the systemic risk measure (equation 17) and the correlation coefficient (reported on Table 12 of the empirical appendix). To complement to that comparison, here follows an account of how both measures fare for the entire period, 1987-2010, and for each of the sub-sample periods. To that effect, I applied the criteria of high pair-wise correlation observed between 1987-1996, and then for the stocks to have been actively traded throughout the entire time length. The resulting qualifying pairs of stocks were those of the two Swedish banks: Nordbanken (re-named Nordea after being listed again in 1997) and SE banken. I constructed the return series for Nordbanken/Nordea by combining the available ln return data I had for both into one return series. Table 6 below summarizes the results.

Table 6 – Correlations and systemic risk measures for Nordbanken/Nordea and SE Banken

Sample period	Pair-wise correlation	$\widehat{SR(k)} - 1$[1]
1987-2010	0.5683[2]	0.1583 (2.43%)[2]
1987-1996[3]	0.2947	0.0000 (0.48%)
1992-2003[4]	0.5953	0.1271 (3.29%)
1997-2010[4]	0.6655	0.3165 (4.06%)

[1] Threshold level: 0.036. In brackets is reported the percentage of observations included when reading the systemic risk estimate at the chosen threshold level.
[2] Calculated using Excel. See file *Corr_SR_comparison_Section6end.xlsx* for further detail. For the systemic risk measure, in the same file, see the sheet named *SR*.
[3] When reading correlation coefficients from Table 12 and looking at systemic risk vs. higher order statistics plots on section 8.7, Nordbanken is B4 and SE Banken is B5.
[4] When reading correlation coefficients from Table 12 and looking at systemic risk vs. higher order statistics plots on section 8.7, Nordea is B3 and SE Banken is B5.

Systemic risk levels for the bank pair rose over the course of the years. Perhaps the threshold selection was not adequate for this particular pair of entities as the systemic risk readings are for only for a minor part of the total number of observations. This is particularly the case for the years 1987-1996. Although as is explained in section 8.4, having to select a threshold levels for all sub-sample periods and for both active and dead stocks, inevitably meant that the chosen threshold would not always be adequate for all pairs of stocks. In this particular case we see that reflected in the selected threshold level only covers a very small part of the data. Over the entire period 1987-2010, the average probability that the two bank crash, given that one crashes, is 15.83% at a threshold level of 3.6%. This high value is driven by the time period 1997-2010 when systemic risk is at the highest.

The correlation coefficient has also increased over the years. In section 2 I mentioned that the correlation coefficient was primarily driven by the observations in the centre of a distribution and that it overstated dependencies at the tail of it. Despite the fact that the correlation coefficient is not adequate to measure dependency at the tail of a distribution, the correlation coefficient here moves in the same direction as the dependency at the tail of the distribution, as measured by the systemic risk measure. Therefore this particular example illustrates that, for these two Swedish banks, systemic risk increased over the years. Giving support to the observation made earlier in this section.

7 Conclusion

The aim of this thesis was to replicate the study by Schoenmaker et al. (2005). In that effort, I first examine, as in the base article by Schoenmaker et al. (2005), whether systemic risk was higher within than across sectors in Scandinavia and second whether the systemic risk levels measured for Europe in the base article, were similar to those observed in Scandinavia at around the same time. The results were not always as expected and systemic risk was found to be lower than expected in the 1987-1996 and 1992-2003 samples. Despite this result, a closer look at the individual return data, renders support to there being higher dependency at the tails of the return distributions than observed in this thesis. Therefore I advanced the suggestion for further study: to use the systemic risk measure with both contemporaneous and lags of return observations.

Nevertheless, the results obtained here answer the above two questions as follows. The answer to the first question is yes, in general and across the samples, systemic risk was higher within sector than across sectors. In this respect, the outcomes reaffirm the outcomes of the base study. With the only exception being the 1992-2003 sample, where the insurance sector was observed to have lower systemic risk average than the cross sector. With regards to the second question, systemic risk measures for Scandinavia for the period 1992-2003 showed the same pattern as found by the authors of the base study but the actual values were not of the same magnitude as those in the base article. Systemic risk in Scandinavia, where observed, was lower than in the rest of Europe (reported in the base study). This could be explained by the Nordic region displaying more national focus than would have been expected by the number of mergers observed. Some of these mergers were cross national and cross sector in nature. Looking across time periods, I observe a distinct increase in systemic risk for the banking sector and to a lesser extent also in the insurance and cross sector. Where systemic risk is observed, it is higher within a country than across borders. Evidence of this is seen in the banking sector and across sectors. A driving factor behind the increase in systemic risk could be the process of deregulation and the market concentration and cross national activities that followed as a result. In the case of Nordic banks, cross border activities manifested themselves as an aggressive expansion into the Baltic countries, Russia and other states of the former Soviet Union. When economic conditions in those regions worsened following the current financial crisis, as in the 1990s crisis, Scandinavian banks had to write off large sums of bad loans. This error of judgement could perhaps be due to the fact that Nordic banks had a history of operating in a very stable and insular financial market (early 1980s) and that following deregulation, the banks have simply failed to fully adapt to having to operate under competitive and global market conditions. Despite this negative note, financial regulation and the business models of Scandinavian banks in combination, could be seen as successful since during the current crisis relatively few banks have had to be rescued – with the exception of some Danish banks.

The univariate replication results for the 1992-2003 and 1997-2010 samples were in broad lines, the same as in the base article, with insurers being found to be more risky than banks. Contrary to the base article, the 1987-1996 sample period produced results in which banks were more risky than insurers. Here, I offered as potential explanation that in the later years market participants had grown to expect troubled banks to be rescued by governments and therefore to be less risky than insurers. Although the explanation was to some extent refuted by the summary statistics of the data.

Pair-wise correlation coefficients have increased over time in Scandinavia and so has systemic risk as registered by the estimates in this thesis. I did bring up the fact that the correlation coefficient is an unsuitable measure for dependencies at the tail of a distribution as the correlation measure is primarily driven by the observations in the centre of a distribution. Therefore, the actual magnitude of the correlation coefficient overestimates the actual dependency we observe during extreme events. Nevertheless, the positive direction in which the correlation coefficient has developed does support that we see an increase in systemic risk as estimated by equation 17.

As argued by Schoenmaker et al. (2005), the fact that systemic risk is lower across than within sectors could be interpreted to mean that there are benefits to bancassurance activities. Maybe the recent calls for and move by banks to divest themselves of their insurance activities might be a premature course of action. Hence the task of drafting adequate policies for regulating financial institutions remains crucial. Bearing in mind that the latest financial crisis triggered the plunge of many economies into a sovereign debt crisis and deepened the ongoing recession, it is ever more important for supervisors to come up with ways to improve their monitoring and coming up with ways to improve information available when drafting regulations. The current financial instability is demonstrating the positive contribution that a systemic risk measure like the one devised in Schoenmaker et al. (2005) can make to guiding policy making.

A word of caution is due with respect to the results reported in this thesis. The quality of the data could not always be reassured and this could possibly distort real stock return relationships as was discussed in section 4.2.6 and in section 8.1.2 of the empirical appendix.

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8 Empirical Appendix

The aim of this empirical appendix is to provide the reader with the necessary information to understand the basis for the results presented and interpretations of these offered in the main sections of this thesis.

8.1 Data selection

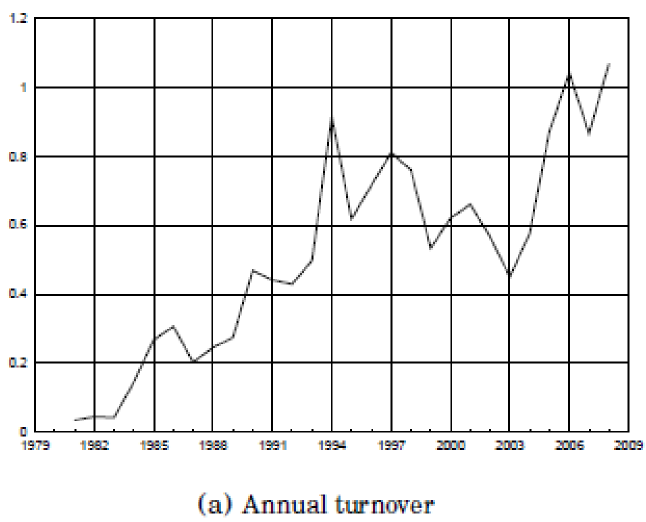
In this section I will discuss how I went about to select the data for this replication study. First I mention the reasons for the choice of study period. Then I will go over problems encountered with respect to the quality of the data. Finally I will present the final list of entities that were selected and reasons why these were selected.

8.1.1 Time period selection

Initially, my intention was to go as far back as to 1980 and collect daily stock price data in order to capture the onset of the financial crisis in Norway which begun in the late 1980s, sooner than the crises in Finland and Sweden. Going as far back as to 1980 would also allow me to capture the effect of the credit market liberalization measures by governments that took place across Scandinavia in the 1980s. Although I suspected that by going as far back in time as intended, I could potentially encounter problems in the quality of the data.

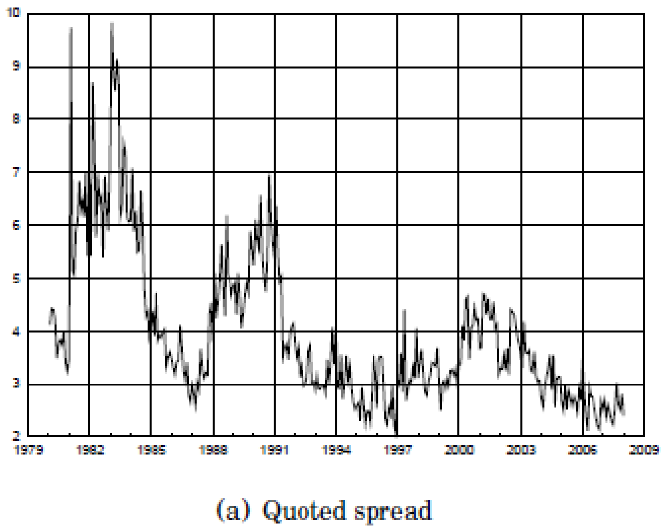
In the 1980s securities trading in Scandinavia was characterized by bulk trading as was the case in the rest of Europe (Roell, A. and Pagano, M. (1990), p. 92). In a liquidity study of the Oslo stock exchange, Næs, Skjeltorp and Ødegaard (2008) find that not only were the early 1980s characterized by low turnover (see Figure 15 below) but they were also characterized by high spreads (see Figure 16 below).

Figure 15 – Annual Turnover at the Oslo stock exchange 1980-2007



Source: Næs et al. (2008), p. 9, Figure 4 a). 'Where, for four size portfolios, daily turnover is measured as daily number of trades divided by the number of shares outstanding. Daily turnover is then aggregated by summing over the year.'

Figure 16 – Daily spreads at the Oslo stock exchange 1979-2009



Source: Næs et al. (2008), p. 14, Figure 6 a). *'The figure shows the time series plot of the cross-sectional average spreads averaged over each month through the sample. ... Figure 6 (a) shows the quoted spread in NOK....'* Quoted spread is measured as *'... the difference between the best ask quote and the best bid quote'* (Ibid, p. 11)

Hence stocks were traded infrequently and trading entailed high costs. From the summary statistics of annual turnover and quoted spreads, the financial sector does relatively worse than other sectors. In a sample of 10 sectors, between 1980-1989, the financial sector mean turnover comes in second place with the lowest turnover and is the third sector with the highest quoted spreads (see Table 7 and Table 8 respectively).

Table 7 – Descriptive statistics for annual turnover

Annual Turnover	Whole sample mean	Whole sample median	1980–1989 mean	1980–1989 median
All securities	61.78	34.04	25.04	13.25
Grouped by industry(GICS)				
10 Energy and consumption	103.55	58.20	37.27	26.21
15 Material/labor	54.31	31.70	24.95	11.34
20 Industrials	52.47	28.84	29.12	18.95
25 Consumer Discretionary	43.28	22.26	22.20	10.41
30 Consumer Staples	40.25	20.25	16.19	9.85
35 Health Care/liability	60.85	43.20	19.67	16.62
40 Financials	44.84	21.09	17.27	9.30
45 Information Technology	95.65	74.79	32.98	15.46
50 Telecommunication Services	71.39	75.68		
55 Utilities	25.87	12.99		

Source: Næs et al. (2008), p. 10, section of Table 2. Sectors are based on GICS industry sectors. Entries for whole sample are for the time period 1980-2007 and for all companies and sizes in sample. *'Daily turnover is measured as the daily number of trades divided by the number of shares outstanding. Daily turnover is then aggregated by summing over the year.'*

Table 8 – Descriptive statistics for quoted spread

Monthly avg BA Spread	Whole sample mean	Whole sample median	1980–1989 mean	1980–1989 median
All securities	4.50	1.82	7.48	3.09
Grouped by industry(GICS)				
10 Energy and consumption	2.37	1.15	4.88	2.04
15 Material/labor	3.86	2.27	5.37	2.59
20 Industrials	5.82	2.27	10.02	2.93
25 Consumer Discretionary	6.92	2.74	7.07	4.62
30 Consumer Staples	5.64	2.29	11.60	5.94
35 Health Care/liability	1.59	1.07	3.07	2.00
40 Financials	6.20	2.97	7.33	4.35
45 Information Technology	2.20	1.03	3.24	2.12
50 Telecommunication Services	2.28	1.91	4.27	4.31
55 Utilities	12.53	1.19		

Source: Næs et al. (2008), p. 42, section of Table 11. Sectors are based on GICS industry sectors. Entries for whole sample are for the time period 1980-2007 and for all companies and sizes in sample.

These facts paint a picture of a stock exchange characterized by low liquidity which could manifest itself as prolonged periods of price stagnation with sudden large price jumps. The price data available from Datastream showed these characteristics. Although, at times and especially for the early 1980s, this price stagnation could last for 60 days or more which suggested errors in the data.

In addition, the financials sectors on the Oslo stock exchange also displayed the lowest numbers of trading days (see Næs et al. (2008), Table 10, p. 41) with a mean of 133.9 and a median of 125.5 days for the period 1980-1989. Therefore the patterns of price persistence observed in the early 1980s data from Datastream, could possibly be attributable to this fact.

Unfortunately I did not succeed in finding similar sources of information that would help me explain the long price constancy in the data for the Danish, Finnish and Swedish stocks. I therefore took the liberty to assume that the same conditions of low liquidity and high spreads observed in Norway applied also to the other Scandinavian countries in the sample.

When generating scatter plots of the ln returns, early 1980s' price data resulted in star-shaped figures. In turn this clouded the true relationship between pairs of stock returns and the outcomes of the systemic risk measure, equation (17). In fact the image emerging was one of little or no correlation and dependence. To avoid this clouding effect, I decided to start the study period in 1987 as it was from this year onwards that the price stagnation was observed but to a lesser degree than in the previous year. The price constancy of early 1980s could very well be due to the reasons stated above but I could not rule out issues in the data collection and registration. As a break point in the data, I decided 1997 was a suitable date as by then most of the nationalized banks had been put back into private hands and were, in general, viewed as sound. I thus ended up with three sample periods 1987-1996, 1997-2010 and one to overlap the time period covered in the base study by Schoenmaker et al. (2005).

8.1.2 Quality of data

To check the quality of the data I turned to additional sources of price data to check against that of Datastream. Bloomberg had daily price data but only for active stocks and bearing in mind I had several dead stocks in my sample this did not always help. For the active stocks available from Bloomberg, nor did the data always go as far back as to 1980. Where Datastream and Bloomberg data did overlap the differences were negligible and I decided to stay with Datastream as a source.

Besides Bloomberg I also used the Thomson One Banker (TOB) database which offers the option not to pad data into nonactive market days. This offered the opportunity to identify those constant prices that were not a result of actual trading. Nevertheless, TOB also did not have access to dead stock prices. Since the price data from Datastream displayed so many, and sometimes long, constant price periods I decided to use the return index (RI) data from Datastream rather than the price data. The RI data has the added advantage that is adjusted for new stock issues and share splits as well as dividend information.[22]

[22] Datastream described the RI calculations as follows: The RI 'shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.' ... 'detailed dividend payment data is only available on Datastream from 1988 onwards. Up to this time the RI is constructed using an annualised dividend yield, as follows:

$$RI_t = RI_{t-1}\left(\frac{PI_t}{PI_{t-1}}\right)\left(1+\frac{DY_t}{PI_{t-1}}\frac{1}{N}\right)$$

Where:

RI_t: return index on day t
RI_{t-1}: return index on previous day
PI_t: price index on day t
PI_{t-1}: price index on previous day
DY_t: dividend yield % on day t

Two other oddities in the data were found: one for the Finnish insurance company Sampo Group and the Danish insurer Codan. In Sampo's case, the company reported daily price data that, at times, differed from the numbers available from Datastream.[23] Therefore for the Sampo Group I have used Sampo's own data instead of that of Datastream. Data for Codan available from Datastream produced a jump in returns of -160% and 160% in a scope of days. I tried to find an explanation for this sudden and extreme jump but was unable to find a possible explanation. Therefore and because it is quite unlikely that such an event would have taken place without it getting documented, I decided to omit those observations from the underlying data. Dates in question were: 23/05/1995 and 24/05/1995.

8.1.3 Selected entities

With regards to the choice of entities, initially, I run a static request on Datastream based on the following search criteria:

- Pre-1987 and active and dead stocks and the same for post-1987
- Stock exchanges: Stockholm (OME), Oslo (OSL), Copenhagen (CSE) and Helsinki (HEL)
- Markets: Sweden, Norway, Denmark and Finland.
- Sectors: Banks (BANKS), Life insurance (LFIN), Nonlife insurance (NLINS) and Financial services (FNSVS).[24]

This returned a high number of qualifying stocks. Therefore, I decided to narrow the selection of entities for the 1987-1996 and 1997-2010 periods by looking at interesting companies. Indeed the pre-requisite was that the selected entities were to be the largest in their countries, in terms of market value. The market value information I gathered from Datastream. This information I combined with information from available literature on the early 1990s financial crisis. For the 1997-2010 period, the basic criteria was also market value but also I kept some of the entities selected for the first sample period in order to observe any changes in systemic risk relationships when moving from one sample period to another. The motivation for including dead stocks in the sample was first and foremost to avoid selection bias. Including dead stocks offered the added bonus of being able to see how the systemic risk measure performed when companies actually went bust. For the period 1992-2003 the sample is made up of those companies present in sample period 1997-2010. Another matter of consideration was the availability of data. In all, the company had to be large, interesting and its data had to be available. Due to the amount of work involved in executing the systemic risk measure, equation (17), and the scope of this thesis, only 5 bank and 5 insurance companies were included in each of the three samples. For full sample lists, see tables 9 and 10 below. These tables

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N: number of working days in the year (taken to be 260).'

'From 1988 onwards:

$RI_t = RI_{t-1}\left(\frac{P_t}{P_{t-1}}\right)$

Except when t= ex-date of the dividend payment D_t then:

$RI_t = RI_{t-1}\left(\frac{P_t+D_t}{P_{t-1}}\right)$

Where:

P_t: price on ex-date

P_{t-1}: price on previous day

D_t: dividend payment associated with ex-date t.'

[23] The Sampo Group's price data was downloaded from: http://www.sampo.com/ir/Share/Historical-Price-Lookup.

[24] In brackets, DS codes. The static request was done for name and ICB Sector Classification Name (ICBSN).

clearly show that the data does not always overlap. For the bivariate systemic risk estimation, this meant that for each pair of stocks, I had to use data only for the time period in which both entities overlapped. For example, for the years 1987-1996 and Danske Bank the total number of observations is 2608 (see Table 14) and systemic risk measures for entity pairs which include Danske Bank are not always of sample size 2608 (see systemic risk estimates including this bank are reported on section 8.5.2 and tables 15, 17, 18 and 20.

Table 9 – Entities for sample period 1987-1996

Name	Country	Name used in section 8.2 and programme files	Data starts	Data ends
Banks				
Christiania Bank	Norway	R_B1	01/01/1980	11/10/1991
Danske Bank	Denmark	R_B2	01/01/1980	19/04/2010
Den norske Bank	Norway	R_B3	01/01/1980	16/11/1992
Nordbanken	Sweden	R_B4	10/08/1984	25/08/1992
SE-Banken	Sweden	R_B5	01/01/1980	19/04/2010
Insurers				
Codan	Denmark	R_I1	01/01/1980	30/07/2007
Hafnia Holding	Denmark	R_I2	17/09/1984	14/08/1992
Sampo	Finland	R_I3	24/04/1989	19/04/2010
Skandia	Sweden	R_I4	04/01/1982	05/06/2006
Storebrand	Norway	R_I5	01/01/1980	19/04/2010

Table 10 – Entities for sample periods 1997-2010 and 1992-2003

Name	Country	Name used in section 8.2 and programme files	Data starts	Data ends
Banks				
Danske Bank[1]	Denmark	R_B1	01/01/1980	19/04/2010
DnB NOR[2]	Norway	R_B2	23/09/1992	19/04/2010
Nordea[3]	Sweden	R_B3	12/08/1997	19/04/2010
Swedbank	Sweden	R_B4	09/06/1995	19/04/2010
SE-Banken	Sweden	R_B5	01/01/1980	19/04/2010
Insurers				
Alm Brand	Denmark	R_I1	01/07/1985	19/04/2010
Codan	Denmark	R_I2	01/01/1980	30/07/2007
Sampo	Finland	R_I3	24/04/1989	19/04/2010
Skandia	Sweden	R_I4	04/01/1982	05/06/2006
Storebrand	Norway	R_I5	01/01/1980	19/04/2010

[1] Danske Bank is what remained of the old Norwegian bank Fokus Bank,
[2] DnB NOR is the successor of Den norske Bank and the other Norwegian bank Nordlandsbanken ASA.
[3] Nordea is what remained of the MeritaNordbanken (itself a merger of Nordbanken and the Finnish bank Merita), the Norwegian bank Christiania Bank and the Dannish bank Unidanmark.

When focusing on interesting characteristics, given the bank was one of the largest in terms of capitalization, I found it valuable to, for the 1987-1996 period, include entities that had been at the receiving end of state support measures during the financial crisis and to include companies that had not or perhaps had seen their troubles through by tapping into capital markets. For the 1997-2010 period I kept those entities in the 1987-1996 sample period that had survived beyond that period and added other qualifying entities that qualified in terms of capitalization. Below follows a brief description of the special characteristics for each the entities included in the 1987-1996 and 1997-2010 sample periods.

1987-1996

Norwegian entities

Christiania Bank, the then largest of the Norwegian banks, was forced to merge with Sunnmørsbanken in January 1990. Sunnmørsbanken was important for Norway to rescue because the bank had significant foreign liabilities and it was feared that a failure of the bank would mean a dry out of foreign capital for other Norwegian banks. In fact, already in 1988, when it was feared the bank's equity would lose all its value by the end of the same year, Sunnmørsbanken was aided by both the Norwegian state and the Norwegian central bank.[25] Christiania Bank, in turn, reported in higher-than-expected losses for the first half of 1991 and received a capital injection of 1,800 million NOK. This effort failed to prevent the bank's net worth dropping below zero in the third quarter of the same year. At the same time, the other Norwegian bank in the sample, Den Norske Bank, which at the time was the country's second largest bank, also received a capital injection from the state. As part of this support, the bank agreed to take over Realkreditt, a mortgage lender (Wilse, 2004 and Honkapohja, 2009). With these capital injections, by the end of 1991, the state was the official owner of both banks. Datastream's data on Christiania Bank therefore runs up to 11 October 1991 and for Den norske Bank up to 16 November 1992.

The insurer Storebrand was at the time, and still is, one of the largest insurers in Scandinavia. Nevertheless, on the 25 August 1992 Storebrand shares were suspended just days after it had acknowledged it required a 1.5 billion NOK capital expansion. In line with what I mentioned in the introduction, the Norwegian finance minister at the time expressed that the insurer's problems were not comparable to those experienced by the banks and that, therefore, the government refrained from intervening. The insurer faced a liquidity shortage which was a result of Storebrand's earlier failed raid on the Swedish insurer Skandia. In early 1993 was again able to report profits and subsequently managed to put the company back on its feet. Storebrand shares were again listed on the Oslo stock exchange on the 18 August 1993 (Fossly et al., 1992 and Fossly, 1992). The gap in the Storebrand data is caused by this suspension of shares.

Swedish entities

In the autumn of 1991, to help Nordbanken, the then third largest commercial bank in the country, meeting capital requirements (9%), the Swedish state injected 4.2 billion SEK of new equity into the bank.[26] By the spring of 1992, having bought out minority holders of the bank (2.1 billion SEK) and having injected yet new capital into the bank (10 billion SEK), the state was the official owner of the bank. In 1993, the state made Nordbanken merge with Götabanken, the fourth largest bank. SE-Banken, the country's then second largest bank, applied for state support but it did not end up using that facility and managed to see out the financial crisis with the help of new capital injections by its existing shareholders (Englund, 1999 and Honkapohja, 2009). Therefore, stock data for Nordbanken runs up to 25 August 1992.

[25] The Norwegian state support was channelled via the Government Bank Investment Fund (SBIF) and administered by the Commercial Banks' Guarantee Fund (CBGF).
[26] State support was administered by the Bank Support Agency (Bankstödsnämnden). Itself set up as a response to the financial crisis.

Skandia was up to 2006, when it was fully acquired by the Brittish Old Mutual Group. Although, it as many other insurers across Scandinavia experienced a significant drop in profitability in 1990, it survived the financial crisis (Lapper, 1992).[27]

Danish entities

Denmark did not suffer a banking crisis of the magnitude observed in the other Nordic countries. In fact, the few banks that experienced bankruptcy were all smaller banks. Nevertheless the number of banks diminished significantly during the crisis, from 270 to just the 200-mark. Unibank [28], Denmark's second largest bank during the 1990s financial crisis was the only one of the largest banks showing signs of liquidity problems by, in 1992, entering into talks with the state and the central bank over possible support measures (Vastrup, 2009 and Honkapohja, 2009). This support was, in the end, not required. In this sample I have included Danske Bank as it was the largest bank in Denmark at the time and because it, as SE-banken in Sweden, managed to sail out the crisis.

With regards to insurers, Codan was at the time of the 1990s crisis one of the largest and managed to see that crisis through. In the summer of 2007, the company fully acquired by the British insurer Royal Sun Alliance. Hafnia Holding, also a major insurer in Denmark, was subject to a takeover by Codan in 1993.

Finnish entities

The Sampo Group is included as it was one of the largest insurers in Finland. It also experienced turbulent times during the financial crisis but managed to survive. The insurer is still active to this day. I thought it would be interesting to include a Finnish company in the sample so that we could have a systemic risk measure outcome that included the country.

1997-2010

With respect to the later sample, the sample remains more or less the same. Of interest is that I have included banks like Nordea and DnB NOR. Nordbanken and Christiania Bank and other companies were merged into Nordea. Den norske Bank was merged together with other banks to form DnB NOR. Therefore, when interpreting the systemic risk measure outcomes of Nordea and DnB NOR, I read those as if they were those of Nordbanken and Den norske Bank and make direct comparisons between the results from one sample to the other.[29] The Swedish bank Swedbank was added as it is currently one of the largest banks in the Nordic region.

The sample for insurers too remains almost in its entirety unchanged from the 1987-1996 sample. Danish insurer Alm Brand has been added as it is a similar-size competitor of Codan. In fact, in 1993, the companies were involved in the bidding for the other Danish insurer, Hafnia Holding (Barnes and Lapper, 1994).

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[27] Insurance companies in Scandinavia were reported to have experienced significant losses made by their reinsurance business activities and because of significant decline in their investment income (Barnes, 1993).

[28] Unibank was the result of a merger in 1990 of Andelsbanken A/S, Privatbanken A/S and SDS Bank A/S.

[29] I could also interpret Nordea's results as corresponding to what the results of Christiania Bank would have been. I decided not to opt for this approach as doing so could lend itself to confusing reading.

8.2 Summary Statistics

8.2.1 General statistics

The underlying names of the entities below referred to can be found on tables 9 and 10 of section 8.1.3.

Table 11 – General Statistics

a) 1987-1996

	R_B1	R_B2	R_B3	R_B4	R_B5	R_I1	R_I2	R_I3	R_I4	R_I5
Mean	-0.0019	0.0004	-0.0033	-0.0006	0.0004	0.0003	-0.0005	0.0000	0.0002	0.0000
Median	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.1422	0.0829	0.5306	0.1636	0.3483	0.1345	0.1211	0.1744	0.1660	0.1205
Minimum	-0.2094	-0.1193	-0.5878	-0.1146	-0.3566	-0.1027	-0.2709	-0.2326	-0.1126	-0.2224
Std. Dev.	0.0277	0.0119	0.0556	0.0229	0.0311	0.0144	0.0240	0.0264	0.0224	0.0257
Skewness	-0.4926	-0.2312	-1.3693	-0.2025	0.4396	0.0773	-2.3421	-0.1190	0.2601	-0.7651
Kurtosis	8.9267	11.4506	34.8793	9.4556	32.2237	14.7584	31.4633	13.4092	8.8877	11.4950
Jarque-Bera	1874.0286	7783.4557	65351.7648	2567.8221	92887.8381	15009.5209	50827.5770	7706.0767	3796.3726	7425.7106
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-2.3724	1.0129	-5.0678	-0.9135	1.1238	0.7795	-0.7464	-0.0179	0.5545	-0.0552
Sum Sq. Dev.	0.9523	0.3701	4.7245	0.7720	2.5252	0.5411	0.8414	1.1852	1.3058	1.5757
Observations	1246	2608	1532	1473	2608	2605	1466	1706	2608	2392

b) 1997-2010

	R_B1	R_B2	R_B3	R_B4	R_B5	R_I1	R_I2	R_I3	R_I4	R_I5
Mean	0.0004	0.0005	0.0004	0.0002	0.0002	0.0000	0.0006	0.0004	0.0004	0.0002
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.1398	0.2549	0.1492	0.1734	0.2322	0.2492	0.1484	0.2082	0.2231	0.2465
Minimum	-0.1719	-0.2050	-0.1220	-0.2054	-0.2231	-0.2378	-0.0774	-0.1823	-0.2464	-0.2187
Std. Dev.	0.0200	0.0241	0.0230	0.0248	0.0266	0.0223	0.0162	0.0230	0.0331	0.0285
Skewness	-0.1372	0.2262	0.3277	-0.0626	0.0985	0.3450	0.6895	0.0515	0.2964	-0.3041
Kurtosis	9.3713	15.9337	7.4790	11.1795	12.0736	17.3944	9.9889	11.2720	9.5299	13.2205
Jarque-Bera	5876.699	24201.81	2753.498	9669.829	11902.26	30009.17	5831.603	9204.628	4403.044	15147.59
Probability	0	0	0	0	0	0	0	0	0	0
Sum	1.5212	1.7162	1.3667	0.6122	0.7956	0.0118	1.6147	1.1797	1.0201	0.6742
Sum Sq. Dev.	1.3804	2.0125	1.7123	2.1258	2.4515	1.7266	0.7245	1.7119	2.6876	2.8167
Observations	3468	3468	3225	3468	3468	3468	2758	3228	2458	3468

c) 1992-2003

	R_B1	R_B2	R_B3	R_B4	R_B5	R_I1	R_I2	R_I3	R_I4	R_I5
Mean	0.0006	0.0007	0.0004	0.0007	0.0006	-0.0004	0.0001	0.0006	0.0002	0.0001
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.1080	0.3365	0.1156	0.1548	0.3483	0.2942	0.1147	0.2082	0.2231	0.1823
Minimum	-0.1183	-0.5878	-0.1220	-0.0772	-0.3566	-0.5793	-0.0886	-0.2326	-0.2464	-0.2187
Std. Dev.	0.0167	0.0258	0.0239	0.0199	0.0316	0.0334	0.0163	0.0272	0.0318	0.0239
Skewness	-0.0860	-2.9873	0.0605	0.3049	0.3962	-1.9493	0.3353	0.2314	0.3133	-0.4938
Kurtosis	7.0183	121.5511	5.3274	5.9431	26.1157	44.3152	8.8583	10.2532	9.3469	13.7859
Jarque-Bera	2109.6548	1726033.3763	358.0096	840.5073	69767.9732	224595.8916	4530.1354	6255.1652	5304.7527	14238.7270
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	1.9176	2.0638	0.5962	1.5721	1.9145	-1.3612	0.2671	1.5908	0.5842	0.1726
Sum Sq. Dev.	0.8735	1.9575	0.9042	0.8867	3.1163	3.5004	0.8324	2.0998	3.1565	1.6567
Observations	3130	2940	1582	2233	3130	3130	3127	2842	3130	2913

8.2.2 Correlation matrices

Table 12 below shows the pair-wise correlation matrices of all stocks and sample periods. Not all pairs of stocks have the same number of observations. Therefore, the correlations below report the correlation of a sample size made up of overlapping observations. For pair-wise sample size see tables 15-17 for the 1987-1996 sample, tables 21-23 for the 1997-2010 sample and tables 27-29 for the 1992-2003 sample. Note that the underlying names of the entities referred to in the correlation matrices below can be found on tables 9 and 10 of section 8.1.3. In Table 12, green coloured boxes represent the correlations within the banking sector, blue those of the insurance sector and red represents the pair-wise correlations observed across sectors.

Table 12 – Correlation matrices

a) 1987-1996

	R_B1	R_B2	R_B3	R_B4	R_B5	R_I1	R_I2	R_I3	R_I4	R_I5
R_B1	1.0000	0.1739	0.5418	0.1253	0.1451	0.1057	0.1031	0.0207	0.1562	0.4210
R_B2	0.1739	1.0000	0.1582	0.1194	0.1147	0.1711	0.2213	0.0453	0.1166	0.1804
R_B3	0.5418	0.1582	1.0000	0.0569	0.1405	0.0674	0.0323	-0.0063	0.1318	0.2844
R_B4	0.1253	0.1194	0.0569	1.0000	0.2947	0.0245	0.0023	0.0509	0.2805	0.1678
R_B5	0.1451	0.1147	0.1405	0.2947	1.0000	0.0329	0.1224	0.1095	0.3062	0.1836
R_I1	0.1057	0.1711	0.0674	0.0245	0.0329	1.0000	0.1681	0.0108	0.0469	0.0547
R_I2	0.1031	0.2213	0.0323	0.0023	0.1224	0.1681	1.0000	0.0187	0.1032	0.0836
R_I3	0.0207	0.0453	-0.0063	0.0509	0.1095	0.0108	0.0187	1.0000	0.0307	0.0688
R_I4	0.1562	0.1166	0.1318	0.2805	0.3062	0.0469	0.1032	0.0307	1.0000	0.1837
R_I5	0.4210	0.1804	0.2844	0.1678	0.1836	0.0547	0.0836	0.0688	0.1837	1.0000

b) 1997-2010

	R_B1	R_B2	R_B3	R_B4	R_B5	R_I1	R_I2	R_I3	R_I4	R_I5
R_B1	1.0000	0.4410	0.4288	0.4262	0.4270	0.2730	0.1698	0.3395	0.2578	0.3349
R_B2	0.4410	1.0000	0.4425	0.4323	0.4673	0.2235	0.1761	0.3586	0.2658	0.4573
R_B3	0.4288	0.4425	1.0000	0.5975	0.6655	0.2064	0.1478	0.3723	0.4175	0.3382
R_B4	0.4262	0.4323	0.5975	1.0000	0.7073	0.2323	0.1280	0.3221	0.3833	0.3693
R_B5	0.4270	0.4673	0.6655	0.7073	1.0000	0.2472	0.1681	0.3416	0.4540	0.3633
R_I1	0.2730	0.2235	0.2064	0.2323	0.2472	1.0000	0.1513	0.1760	0.1069	0.1796
R_I2	0.1698	0.1761	0.1478	0.1280	0.1681	0.1513	1.0000	0.1184	0.1439	0.1624
R_I3	0.3395	0.3586	0.3723	0.3221	0.3416	0.1760	0.1184	1.0000	0.2507	0.2723
R_I4	0.2578	0.2658	0.4175	0.3833	0.4540	0.1069	0.1439	0.2507	1.0000	0.2671
R_I5	0.3349	0.4573	0.3382	0.3693	0.3633	0.1796	0.1624	0.2723	0.2671	1.0000

c) 1992-2003

	R_B1	R_B2	R_B3	R_B4	R_B5	R_I1	R_I2	R_I3	R_I4	R_I5
R_B1	1.0000	0.1500	0.3123	0.2635	0.1694	0.1173	0.1276	0.1759	0.2282	0.2233
R_B2	0.1500	1.0000	0.3021	0.2815	0.1161	0.0095	0.1048	0.1621	0.1792	0.3454
R_B3	0.3123	0.3021	1.0000	0.5416	0.5956	0.0869	0.1253	0.2462	0.4302	0.2116
R_B4	0.2635	0.2815	0.5416	1.0000	0.5619	0.0784	0.0902	0.2238	0.3829	0.2084
R_B5	0.1694	0.1161	0.5956	0.5619	1.0000	0.0844	0.0775	0.1777	0.3358	0.2147
R_I1	0.1173	0.0095	0.0869	0.0784	0.0844	1.0000	0.0849	0.0261	0.0886	0.0489
R_I2	0.1276	0.1048	0.1253	0.0902	0.0775	0.0849	1.0000	0.0649	0.1110	0.1110
R_I3	0.1759	0.1621	0.2462	0.2238	0.1777	0.0261	0.0649	1.0000	0.1835	0.1385
R_I4	0.2282	0.1792	0.4302	0.3829	0.3358	0.0886	0.1110	0.1835	1.0000	0.2394
R_I5	0.2233	0.3454	0.2116	0.2084	0.2147	0.0489	0.1110	0.1385	0.2394	1.0000

8.3 Random variable generation

This section will cover the specific calculations used when generating the random normal and student-t distributed variables for which results are presented in the main text of this thesis.

8.3.1 Bivariate normal distributed variables

I start by randomly generating normal distributed variables using Eviews. By normalizing these, I make absolutely sure that for variables X and Y:

$X \sim N(0,1)$ and $Y \sim N(0,1)$

Thus:

$$\mu_X = E[X] = 0 \qquad \mu_Y = E[Y] = 0$$

$$\sigma_X^2 = E[(X-\mu_X)^2] = E[X^2] = 1 \qquad (18) \qquad \sigma_Y^2 = E[(Y-\mu_Y)^2] = E[Y^2] = 1$$

And because X and Y are independent:

$$Cov(X,Y) = E[XY] - \mu_X\mu_Y = 0$$

And variable Z is a sum of X and Y and is normal distributed:

$$Z = aX + bY$$

Thus:

$$\mu_Z = E[aX + bY] = aE[X] + bE[Y] = 0$$

$$\begin{aligned} \sigma_Z^2 = {} & E[(aX+bY)^2] = E[a^2X^2 - 2abXY + b^2Y^2] \\ & = a^2E[X^2] - 2abE[XY] + b^2E[Y^2] = a^2 + b^2 \end{aligned} \qquad (19)$$

$$\begin{aligned} Cov(X,Z) = {} & Cov[X,(aX+bY)] = E[X(aX+bY)] \\ & = E[aX^2 + bXY] = aE[X^2] + bE[XY] = a \end{aligned} \qquad (20)$$

And using equations (18), (19) and (20) above:

$$\rho_{XZ} = \frac{Cov(X,Z)}{\sigma_X\sigma_Z} = \frac{a}{\sqrt{1}\sqrt{a^2+b^2}} = \frac{a}{\sqrt{a^2+b^2}} \qquad (21)$$

Then I equal equation (19) above with the variance of the second variable (Y_{RD}) in the raw data and I equal equation (21) above with the correlation coefficient of the raw data ($\rho_{X_{RD}Y_{RD}}$). The calculations were:

Solving for *a:*

$$a^2 + b^2 = \sigma_{Y_{RD}}^2$$

$$a = \sqrt{\sigma_{Y_{RD}}^2 - b^2} \qquad (22)$$

Solving for *b* and replacing *a* with equation (22) here next:

$$\frac{a}{\sqrt{a^2+b^2}} = \rho_{X_{RD}Y_{RD}}$$

$$\rho_{X_{RD}Y_{RD}} = \sqrt{\sigma_{Y_{RD}}^2 - b^2} \Big/ \sqrt{\sigma_{Y_{RD}}^2 - b^2 + b^2}$$

$$\rho_{X_{RD}Y_{RD}} = \sqrt{\sigma_{Y_{RD}}^2 - b^2} / \sigma_{Y_{RD}}$$

$$\rho_{X_{RD}Y_{RD}}^2 \sigma_{Y_{RD}}^2 = \sigma_{Y_{RD}}^2 - b^2$$

$$b = \sigma_{Y_{RD}}(1 - \rho_{X_{RD}Y_{RD}}^2)^{1/2}$$

With a and b I can now create a series for Z. I then create yet two new variables, X_{new} and Y_{new}, which take across the mean standard deviation and variance of the raw data entities pair. I also make use of the random generated normal distributed variables I begun with.[30]

For X_{RD} I get: $X_{new} = \left(X * \sigma_{X_{RD}}\right) + \mu_{X_{RD}}$

For Y_{RD} I get: $Y_{new} = Z + \mu_{Y_{RD}}$

The last thing I did was to plot X_{new} against Y_{new} which resulted with figures in the style of Figure 5 shown in section 4.[31]

8.3.2 Student-t distributed variables

For the student-t distributed variables, again I used Eviews and specified 3 degrees of freedom (v). I call these $R_{t,i}^{E}$, where i stands for ith observation. In order to force those generated series to have a mean of zero and variance of $v/(v-2)$, I re-scaled the $R_{t,i}^{E}$ observations as follows

$$R_{t,i} = \left[R_{t,i}^{E} - \bar{R}_{t}^{E}\right] / \left[\sigma_{R_t^E} \frac{v}{(v-2)}\right]$$

Where:

$R_{t,i}$: is the ith observation of a student-t distributed variable with mean of zero and variance of $v/(v-2)$.

$\bar{R}_{t}^{E}$: is the mean of the random generated student-t distributed variable originally made by Eviews.

$\sigma_{R_t^E}$: Is the standard deviation of the random generated student-t distributed variable originally made by Eviews.

Following these steps, I now had series pairs as:

$X \sim t[0, M]$ and $Y \sim t[0, N]$

Where M and N are equal to $v/(v-2)$. Thus:

$\mu_X = E[X] = 0$ $\quad\quad$ $\mu_Y = E[Y] = 0$

$$\sigma_X^2 = E[(X - \mu_X)^2] = E[X^2] = M \quad (23) \quad \sigma_Y^2 = E[(Y - \mu_Y)^2] = E[Y^2] = N$$

And because X and Y are independent:

$$Cov(X, Y) = \quad E[XY] - \mu_X \mu_Y = 0$$

And variable Z is a sum of X and Y and is normal distributed:

$$Z = aX + bY$$

Thus:

[30] In the Eviews program file, when handling the combinations of stocks within sectors, I have called Z, Z_BiBj. Where *i* runs from 1-4 and *j* from 2-5 and where *B* is changed to "I" when dealing with insurances. For the cross sector exercise, Z is called z_BiIj. Where both *i* and *j* run from 1-5.

[31] Checks were carried out to compare the correlation coefficient of the pair-wise generated data with that of the original data pair and they only differed to a minor extent. For example in 1997-2010 the real data pair-wise correlation between bank 1 and 2 was 0.4410 and that of the bivariate normal generated data was 0.4452.

$$\mu_Z = E[aX + bY] = aE[X] + bE[Y] = 0$$

$$\sigma_Z^2 = \quad E[(aX + bY)^2] = E[(a^2X^2 - 2abXY + b^2Y^2)] = a^2E[X^2] - 2abE[XY] + b^2E[Y^2]$$
$$= a^2 + b^2 = a^2E[X^2] - 2abE[XY] + b^2E[Y^2] = a^2M + b^2N \tag{24}$$

$$Cov(X,Z) = \quad Cov[X,(aX + bY)] = E[X(aX + bY)] = E[aX^2 + bXY] = aE[X^2] + bE[XY]$$
$$= aM \tag{25}$$

And using equations (23), (24) and (25) above:

$$\rho_{XZ} = \quad \frac{Cov(X,Z)}{\sigma_X \sigma_Z} = \frac{aM}{\sqrt{M}\sqrt{a^2M + b^2N}} \tag{26}$$

As before, I solved for b and a by equalling equation (24) with the variance of the second variable (Y_{RD}) in the raw data and by equalling equation (26) with the correlation coefficient of the raw data ($\rho_{X_{RD}Y_{RD}}$). The results were:

Solving for b:

$$a^2M + b^2N = \sigma_{Y_{RD}}^2$$

$$b^2 = \left(\sigma_{Y_{RD}}^2 - a^2M\right)/N$$

$$b = \sqrt{\left(\sigma_{Y_{RD}}^2 - a^2M\right)/N} \tag{27}$$

Solving for a and replacing a with equation (27) here next:

$$\frac{aM}{\sqrt{M}\sqrt{a^2M + b^2N}} = \rho_{X_{RD}Y_{RD}}$$

$$\rho_{X_{RD}Y_{RD}} = \frac{a\sqrt{M}}{\sqrt{a^2M + \frac{(\sigma_{Y_{RD}}^2 - a^2M)}{N}N}}$$

$$\rho_{X_{RD}Y_{RD}} = \frac{a\sqrt{M}}{\sigma_{Y_{RD}}}$$

$$a = \frac{\rho_{X_{RD}Y_{RD}} * \sigma_{Y_{RD}}}{\sqrt{M}}$$

With values for a and b I could now create a series for variable Z. I then created yet two new variables X_{new} and Y_{new} which take across the mean standard deviation and variance of the raw data entities pair. I also make use of the random generated student-t distributed variable X.

For X_{RD} I get: $$X_{new} = \frac{\left(X * \sigma_{X_{RD}}\right)}{M} + \mu_{X_{RD}}$$

For Y_{RD} I get: $$Y_{new} = Z + \mu_{Y_{RD}}$$

The last thing I did was to plot X_{new} against Y_{new} which resulted with figures in the style of Figure 6 shown in section 4.[32]

[32] Checks were carried out to compare the correlation coefficient of the pair-wise generated data with that of the original data pair and they only differed to a minor extent. For example in 1997-2010 the real data pair-wise correlation between bank 1 and 2 was 0.4410 and that of the student-t generated data was 0.4322.

8.4 Systemic risk measure: threshold selection

When choosing a threshold level to report results on the systemic risk measure, equation (17),the procedure to take is similar to the eyeball method described for the Hill estimator in section 3.1. For pairs of stocks, higher order statistics are plotted against the systemic risk measure. This resulted in figures like the one depicted in Figure 13. For a full list of all resulting $\widehat{SR(k)} - 1$ vs. higher order statistics plots see section 8.7 of this empirical appendix. In an attempt to minimise the MSE, I then look for the first opportunity where I see the systemic risk measure stabilizing having first been unstable far out at the tail of the distribution. I then read the corresponding threshold level for the pair of stocks. This because I am effectively measuring in the middle of the distribution where dependency increases. The threshold series, in turn, are an average of the higher order statistics of each pair of stock returns. A first glance at the resulting scatter plot figures reveals that for the periods 1987-1996 and 1992-2003 there is little dependency observed at the tails. For the period 1997-2010, on the other hand, a higher degree of dependency is observed. I therefore decided to report on a threshold level that was suitable for the entities for which I observed dependency at the tails. The result of that exercise is reported on Table 13 below. Taking all entities into account when choosing a threshold level would have meant that for those entity pairs that show dependency in the tail, making threshold readings too far into the centre of their distribution. Meaning I would no longer be looking at dependency at the extreme for those entities. Results would have then suffered from upward bias as too many observations in the middle of the distribution would be included. On the other hand, choosing a threshold suitable only for those entities that show dependency at the tails, also presents me the problem of having chosen a threshold level that for some pairs is too high. Therefore, in those instances I simply do not find any number of observations that exceed that threshold (and I am actually trying to measure outside the distribution) and the count measure for systemic risk comes back with an error. Alternatively, where the chosen threshold level is too high, I could end up with too few observations exceeding the threshold level and I end up with the problem of high variance. The choice of threshold to report on for such a large period of time would always be tricky. Yet I believe my approach to be a sound one bearing in mind the peculiarities of the data in question. As Table 13 below shows, for the entities where systemic risk is observed at the tails, the resulting average threshold level corresponding to regions where systemic risk stabilizes is 3.6%. This is the threshold level I report multivariate results on in section 0.

Table 13 – Threshold levels for observed stable levels of SR(k)-1

Sample	Company pair	SR(k)-1	Corresponding threshold level	Corresponding Higher Order Statistics	Total number of observations	Average threshold level
1987-1996						
	Christiania Bank vs. Den norske Bank	0.0297	0.0233	90	1246	**0.0233**
1997-2010						
	Danske Bank vs. DnB NOR	0.1018	0.0254	125	3468	
	Danske Bank vs. Nordea	0.0479	0.0366	50	3225	
	Danske Bank vs. Swedbank	0.0549	0.0392	53	3468	
	Danske Bank vs. SE Banken	0.0588	0.0389	60	3468	
	DnB NOR vs. Nordea	0.0966	0.0348	60	3225	
	DnB NOR vs. Swedbank	0.0829	0.0375	52	3468	
	DnB NOR vs. SE Banken	0.1183	0.0394	65	3468	
	Nordea vs. Swedbank	0.1765	0.0454	50	3225	
	Nordea vs. SE Banken	0.2973	0.0407	105	3225	
	Swedbank vs. SE Banken	0.2581	0.0548	48	3468	**0.0393**
1992-2003						
	Nordea vs. Swedbank	0.1927	0.0211	98	1582	
	Nordea vs. SE Banken	0.1895	0.0315	67	1582	
	Swedbank vs. SE Banken	0.1282	0.0308	75	2233	**0.0278**
					All samples	**0.0357**

8.5 Results

8.5.1 Univariate results

All Hill plots which Table 14 is based on, are depicted on section 8.6 of this empirical appendix.

Table 14 – Hill estimator selection and univariate probabilities estimations

Sample	Company name	Higher order statistic, m	Sample size, n	X_{m+1} higher order statistic (absolute value)	Threshold loss, x_{var}, at 15% (absolute value)	Tail index estimate, $\hat{\alpha}_{(m)}$	Probability, $\hat{p}$
1987-1996							
	Christiania Bank	72	1246	0.04381	0.15000	2.65756	0.00219
	Danske Bank	101	2608	0.01921	0.15000	2.75681	0.00013
	Den norske Bank	56	1532	0.07637	0.15000	1.43387	0.01389
	Nordbanken	84	1473	0.03307	0.15000	2.05930	0.00253
	SE-Banken	50	2608	0.05916	0.15000	2.25630	0.00235
	Codan	64	2605	0.03142	0.15000	2.57520	0.00044
	Hafnia Holding	95	1466	0.02665	0.15000	1.78170	0.00298
	Sampo Group	86	1706	0.03922	0.15000	2.31708	0.00225
	Skandia	80	2608	0.04177	0.15000	2.85600	0.00080
	Storebrand	53	2392	0.05782	0.15000	2.68961	0.00171
					Average	**2.33834**	**0.00293**
1997-2010							
	Danske Bank	90	3468	0.03974	0.15000	2.88648	0.00056
	DnB NOR	95	3468	0.04447	0.15000	2.57414	0.00120
	Nordea	104	3225	0.04137	0.15000	3.00066	0.00068
	Swedbank	57	3468	0.05824	0.15000	2.75741	0.00121
	SE-Banken	122	3468	0.04445	0.15000	2.62706	0.00144
	Alm Brand	96	3468	0.04229	0.15000	2.84277	0.00076
	Codan	104	2758	0.02632	0.15000	2.77062	0.00030
	Sampo Group	51	3228	0.05176	0.15000	2.91732	0.00071
	Skandia	82	2458	0.06032	0.15000	3.17297	0.00185
	Storebrand	60	3468	0.06324	0.15000	2.39260	0.00219
					Average	**2.79420**	**0.00109**
1992-2003							
	Danske Bank	77	3130	0.03367	0.15000	3.26551	0.00019
	DnB NOR	52	2940	0.04476	0.15000	2.40534	0.00096
	Nordea	105	1582	0.03289	0.15000	2.79118	0.00096
	Swedbank	88	2233	0.03291	0.15000	3.51989	0.00019
	SE-Banken	85	3130	0.05191	0.15000	2.35158	0.00224
	Alm Brand	58	3130	0.07427	0.15000	2.40525	0.00342
	Codan	90	3127	0.03243	0.15000	2.98257	0.00030
	Sampo Group	101	2842	0.04637	0.15000	3.15452	0.00088
	Skandia	95	3130	0.05990	0.15000	3.20773	0.00160
	Storebrand	54	3130	0.05237	0.15000	2.56399	0.00116
					Average	**2.86475**	**0.00119**

8.5.2 Pair wise multivariate results

Here follows a list of tables listing the results for the three sample periods. For each sample period results are reported for the real data, bivariate normal and student-t distributed data.

1987-1996 sample period, real data

Table 15 – Banks vs. Banks, $\widehat{SR(k)} - 1$, t=0.036, real data

	Christiania Bank	Danske Bank	Den norske Bank	Nordbanken	SE Banken	**Average**
Christiania Bank						
Danske Bank	0.0000 (3; 1246)					
Den norske Bank	0.1563 (30; 1246)	0.0165 (50; 1532)				
Nordbanken	0.0000 (9; 1246)	0.0000 (11; 1473)	0.0000 (10; 1473)			
SE Banken	0.0000 (5; 1246)	0.0000 (42; 2608)	0.0000 (10; 1532)	0.0000 (7; 1473)		**0.0173**

In brackets: (corresponding higher order statistics; total number of observations)

Table 16 – Insurers vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, real data

	Codan	Hafnia Holding	Sampo	Skandia	Storebrand	**Average**
Codan						
Hafnia Holding	0.0000 (14; 1466)					
Sampo	0.0000 (26; 1704)	0.0000 (7; 674)				
Skandia	0.0000 (17; 2605)	0.0000 (12; 1466)	0.0000 (10; 1706)			
Storebrand	0.0000 (32; 2389)	0.0000 (27; 1466)	0.0000 (16; 1521)	0.0000 (36; 2392)		**0.0000**

In brackets: (corresponding higher order statistics; total number of observations)

Table 17 – Banks vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, real data

	Christiania Bank	Danske Bank	Den norske Bank	Nordbanken	SE Banken	**Average**
Codan	0.0000 (2; 1246)	0.0000 (5; 2605)	0.0000 (9; 1532)	0.0000 (2; 1473)	0.0000 (4; 2605)	
Hafnia Holding	0.0000 (7; 1246)	0.0000 (14; 1466)	0.0000 (14; 1466)	0.0000 (13; 1466)	0.0000 (14; 1466)	
Sampo	0.0000 (3; 504)	0.0000 (26; 1706)	0.0000 (15; 726)	0.0000 (8; 678)	0.0089 (27; 1706)	
Skandia	0.0000 (9; 1246)	0.0000 (19; 2608)	0.0412 (26; 1532)	0.0000 (14; 1473)	0.0490 (41; 2608)	
Storebrand	0.0658 (26; 1246)	0.0000 (29; 2392)	0.0744 (47; 1471)	0.0000 (26; 1471)	0.0000 (30; 2392)	**0.0096**

In brackets: (corresponding higher order statistics; total number of observations)

1987-1996, bivariate normal data

Table 18 – Banks vs. Banks, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Christiania Bank	Danske Bank	Den norske Bank	Nordbanken	SE Banken	**Average**
Christiania Bank						
Danske Bank	0.0000 (1; 1246)					
Den norske Bank	0.0187 (27; 1246)	0.0000 (138; 1532)				
Nordbanken	0.0000 (1; 1246)	0.0000 (2; 1473)	0.0000 (2; 1473)			
SE Banken	0.0000 (1; 1246)	0.0000 (39; 2608)	0.0000 (3; 1532)	0.0000 (3; 1473)		**0.0019**

In brackets: (corresponding higher order statistics; total number of observations)

Table 19 – Insurers vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Codan	Hafnia Holding	Sampo	Skandia	Storebrand	**Average**
Codan						
Hafnia Holding	0.0000 (4; 1466)					
Sampo	0.0000 (8; 1704)	0.0000 (1; 674)				
Skandia	0.0000 (2; 2605)	0.0000 (2; 1466)	0.0000 (1; 1706)			
Storebrand	0.0000 (8; 2389)	0.0000 (12; 1466)	0.0000 (12; 1521)	0.0000 (8; 2392)		**0.0000**

In brackets: (corresponding higher order statistics; total number of observations)

Table 20 – Banks vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Christiania Bank	Danske Bank	Den norske Bank	Nordbanken	SE Banken	**Average**
Codan	0.0000 (1; 1246)	0.0000 (1; 2605)	0.0000 (1; 1532)	0.0000 (1; 1473)	0.0000 (1; 2605)	
Hafnia Holding	0.0000 (1; 1246)	0.0000 (6; 1466)	0.0000 (1; 1466)	0.0000 (2; 1466)	0.0000 (3; 1466)	
Sampo	0.0000 (1; 504)	0.0000 (6; 1706)	0.0000 (5; 726)	0.0000 (2; 678)	0.0000 (7; 1706)	
Skandia	0.0000 (2; 1246)	0.0000 (3; 2608)	0.0000 (2; 1532)	0.0000 (5; 1473)	0.0000 (3; 2608)	
Storebrand	0.0083 (19; 1246)	0.0000 (8; 2392)	0.0000 (15; 1471)	0.0000 (17; 1471)	0.0000 (11; 2392)	**0.0003**

In brackets: (corresponding higher order statistics; total number of observations)

1997-2010 sample period, real data

Table 21 – Banks vs. Banks, $\widehat{SR(k)} - 1$, t=0.036, real data

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Danske Bank						
DnB NOR	0.0568 (64; 3468)					
Nordea	0.0471 (51; 3225)	0.0872 (58; 3225)				
Swedbank	0.0573 (58; 3468)	0.0816 (61; 3225)	0.2000 (92; 3225)			
SE Banken	0.0633 (71; 3468)	0.1071 (76; 3468)	0.3165 (131; 3225)	0.2869 (129; 3468)		**0.1304**

In brackets: (corresponding higher order statistics; total number of observations)

Table 22 – Insurers vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, real data

	Alm Brand	Codan	Sampo	Skandia	Storebrand	**Average**
Alm Brand						
Codan	0.0000 (8; 2758)					
Sampo	0.0000 (29; 3228)	0.0000 (20; 2563)				
Skandia	0.0000 (60; 2458)	0.0000 (57; 2458)	0.0083 (60; 2281)			
Storebrand	0.0000 (65; 3468)	0.0000 (20; 2758)	0.0089 (72; 3228)	0.0164 (23; 2458)		**0.0034**

In brackets: (corresponding higher order statistics; total number of observations)

Table 23 – Banks vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, real data

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Alm Brand	0.0000 (23; 3468)	0.0360 (37; 3468)	0.0000 (32; 3225)	0.0192 (36; 3468)	0.0248 (38; 3468)	
Codan	0.0000 (8; 2758)	0.0000 (9; 2758)	0.0000 (7; 2515)	0.0000 (9; 2758)	0.0000 (8; 2758)	
Sampo	0.0061 (32; 3228)	0.0599 (44; 3228)	0.0325 (44; 2998)	0.0235 (41; 3228)	0.0511 (54; 3228)	
Skandia	0.0000 (56; 2458)	0.0000 (56; 2458)	0.0000 (59; 2215)	0.0000 (63; 2458)	0.0000 (65; 2458)	
Storebrand	0.0000 (68; 3468)	0.0460 (80; 3468)	0.0044 (72; 3225)	0.0210 (71; 3468)	0.0502 (76; 3468)	**0.0150**

In brackets: (corresponding higher order statistics; total number of observations)

1997-2010, bivariate normal data

Table 24 – Banks vs. Banks, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Danske Bank						
DnB NOR	0.0000 (28; 3468)					
Nordea	0.0000 (22; 3225)	0.0000 (23; 3225)				
Swedbank	0.0041 (46; 3468)	0.0041 (30; 3225)	0.0927 (81; 3225)			
SE Banken	0.0000 (60; 3468)	0.0065 (60; 3468)	0.1429 (148; 3225)	0.1847 (136; 3468)		**0.0435**

In brackets: (corresponding higher order statistics; total number of observations)

Table 25 – Insurers vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Alm Brand	Codan	Sampo	Skandia	Storebrand	**Average**
Alm Brand						
Codan	0.0000 (1; 2758)					
Sampo	0.0000 (5; 3228)	0.0000 (1; 2563)				
Skandia	0.0000 (37; 2458)	0.0000 (39; 2458)	0.0000 (56; 2281)			
Storebrand	0.0000 (18; 3468)	0.0000 (5; 2758)	0.0000 (56; 3228)	0.0000 (6; 2458)		**0.0000**

In brackets: (corresponding higher order statistics; total number of observations)

Table 26 – Banks vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Alm Brand	0.0000 (5; 3468)	0.0000 (8; 3468)	0.0000 (5; 3225)	0.0000 (3; 3468)	0.0000 (1; 3468)	
Codan	0.0000 (1; 2758)	0.0000 (1; 2758)	0.0000 (1; 2515)	0.0000 (1; 2758)	0.0000 (1; 2758)	
Sampo	0.0000 (8; 3228)	0.0000 (18; 3228)	0.0000 (7; 2998)	0.0000 (13; 3228)	0.0000 (12; 3228)	
Skandia	0.0000 (52; 2458)	0.0000 (41; 2458)	0.0206 (98; 2215)	0.0028 (85; 2458)	0.0341 (102; 2458)	
Storebrand	0.0000 (44; 3468)	0.0108 (88; 3468)	0.0027 (64; 3225)	0.0000 (58; 3468)	0.0000 (52; 3468)	**0.0028**

In brackets: (corresponding higher order statistics; total number of observations)

1992-2003 sample period, real data

Table 27 – Banks vs. Banks, $\widehat{SR(k)}-1$, t=0.036, real data

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Danske Bank						
DnB NOR	0.0000 (26; 2940)					
Nordea	0.0106 (18; 1582)	0.0000 (19; 1582)				
Swedbank	0.0000 (13; 2233)	0.0000 (11; 2233)	0.0758 (23; 1582)			
SE Banken	0.0000 (59; 3130)	0.0000 (52; 2940)	0.1271 (52; 1582)	0.0956 (51; 2233)		**0.0309**

In brackets: (corresponding higher order statistics; total number of observations)

Table 28 – Insurers vs. Insurers, $\widehat{SR(k)}-1$, t=0.036, real data

	Alm Brand	Codan	Sampo	Skandia	Storebrand	**Average**
Alm Brand						
Codan	0.0000 (9; 3127)					
Sampo	0.0000 (42; 2842)	0.0000 (41; 2840)				
Skandia	0.0000 (66; 3130)	0.0000 (64; 3127)	0.0000 (64; 2842)			
Storebrand	0.0000 (24; 3130)	0.0000 (25; 2910)	0.0000 (25; 2656)	0.0063 (29; 3130)		**0.0006**

In brackets: (corresponding higher order statistics; total number of observations)

Table 29 – Banks vs. Insurers, $\widehat{SR(k)}-1$, t=0.036, real data

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Alm Brand	0.0000 (71; 3130)	0.0000 (67; 2940)	0.0000 (16; 1582)	0.0000 (19; 2233)	0.0000 (69; 3130)	
Codan	0.0000 (9; 3127)	0.0000 (10; 2937)	0.0000 (5; 1582)	0.0000 (6; 2233)	0.0000 (8; 3127)	
Sampo	0.0000 (42; 2842)	0.0096 (39; 2699)	0.0000 (18; 1457)	0.0000 (20; 2059)	0.0089 (45; 2842)	
Skandia	0.0000 (65; 3130)	0.0035 (61; 2940)	0.0000 (58; 1582)	0.0000 (62; 2233)	0.0163 (88; 3130)	
Storebrand	0.0000 (24; 3130)	0.0000 (31; 2940)	0.0000 (17; 1582)	0.0000 (16; 2233)	0.0000 (28; 3130)	**0.0015**

In brackets: (corresponding higher order statistics; total number of observations)

1992-2003 sample period, bivariate normal data

Table 30 – Banks vs. Banks, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Danske Bank						
DnB NOR	0.0000 (15; 2940)					
Nordea	0.0000 (7; 1582)	0.0000 (7; 1582)				
Swedbank	0.0000 (6; 2233)	0.0000 (1; 2233)	0.0000 (6; 1582)			
SE Banken	0.0000 (51; 3130)	0.0000 (39; 2940)	0.0593 (35; 1582)	0.0325 (32; 2233)		**0.0092**

In brackets: (corresponding higher order statistics; total number of observations)

Table 31 – Insurers vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

	Alm Brand	Codan	Sampo	Skandia	Storebrand	**Average**
Alm Brand						
Codan	0.0000 (1; 3127)					
Sampo	0.0000 (13; 2842)	0.0000 (11; 2840)				
Skandia	0.0000 (45; 3130)	0.0000 (47; 3127)	0.0000 (52; 2842)			
Storebrand	0.0000 (4; 3130)	0.0000 (3; 2910)	0.0000 (6; 2656)	0.0000 (4; 3130)		**0.0000**

In brackets: (corresponding higher order statistics; total number of observations)

Table 32 – Banks vs. Insurers, $\widehat{SR(k)} - 1$, t=0.036, bivariate normal

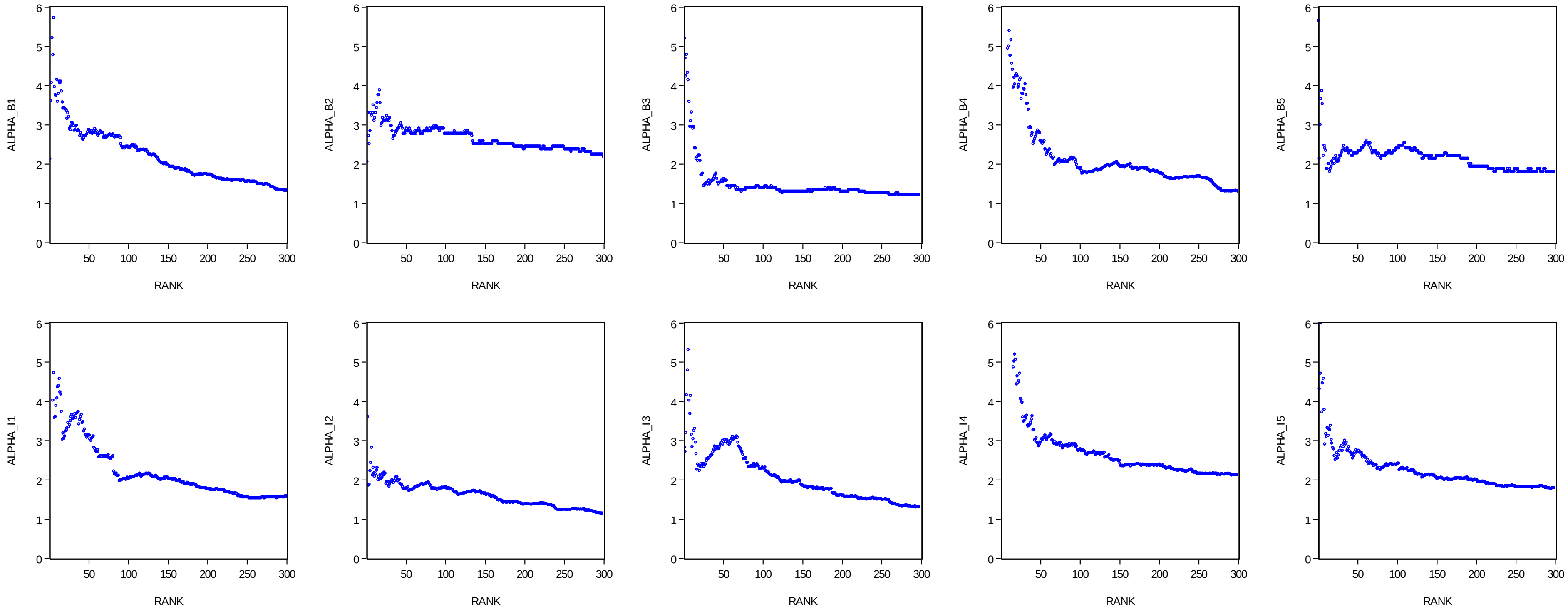
	Danske Bank	DnB NOR	Nordea	Swedbank	SE Banken	**Average**
Alm Brand	0.0000 (48; 3130)	0.0000 (42; 2940)	0.0000 (2; 1582)	0.0000 (2; 2233)	0.0000 (43; 3130)	
Codan	0.0000 (1; 3127)	0.0000 (1; 2937)	0.0000 (1; 1582)	0.0000 (1; 2233)	0.0000 (1; 3127)	
Sampo	0.0000 (10; 2842)	0.0000 (15; 2699)	0.0000 (18; 1457)	0.0000 (7; 2059)	0.0000 (15; 2842)	
Skandia	0.0000 (57; 3130)	0.0000 (39; 2940)	0.0514 (110; 1582)	0.0217 (86; 2233)	0.0000 (68; 3130)	
Storebrand	0.0000 (6; 3130)	0.0000 (4; 2940)	0.0000 (11; 1582)	0.0000 (6; 2233)	0.0000 (6; 3130)	**0.0029**

In brackets: (corresponding higher order statistics; total number of observations)

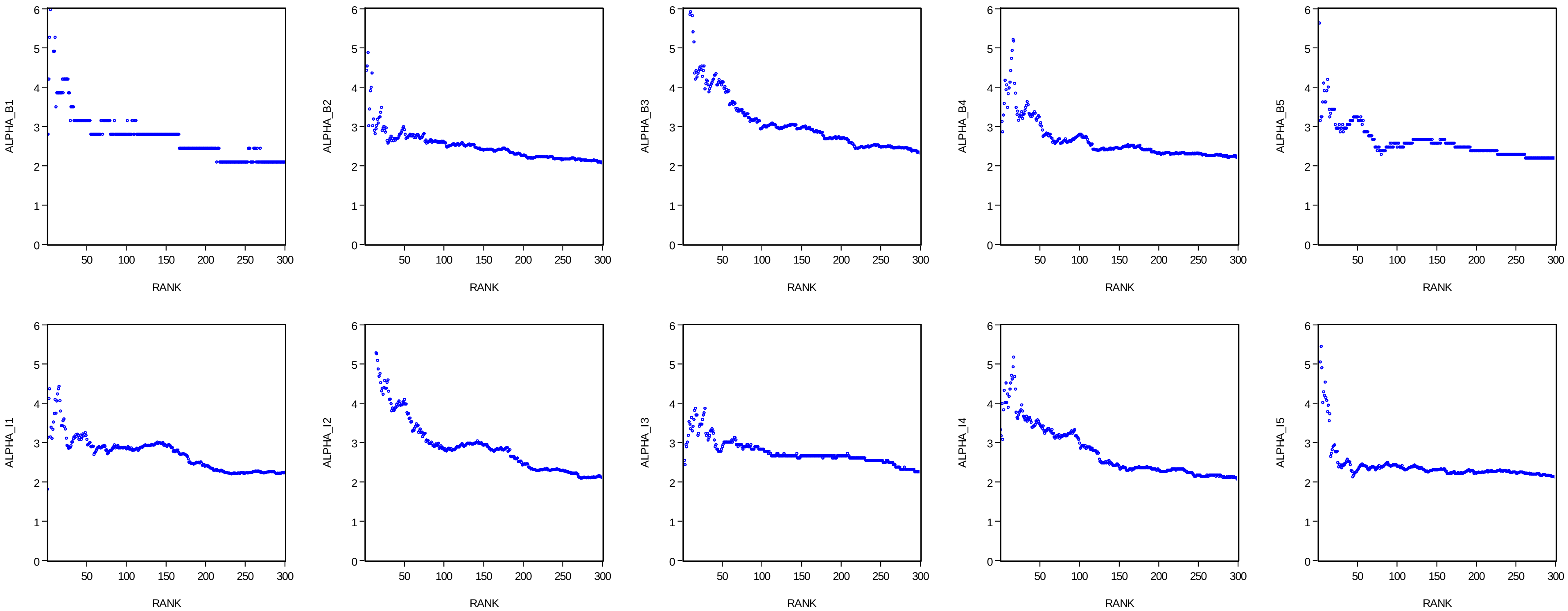
8.6 Hill plots

Below are the Hill plots for all entities and all sample periods and where the names *ALPHA_B1* stands for the Hill estimator of bank 1 and *ALPHA_I1* stands for the Hill estimator of insurer 1. For a list of the bank and insurer names in each sample period, see tables 8 and 9 on section 8.1.3

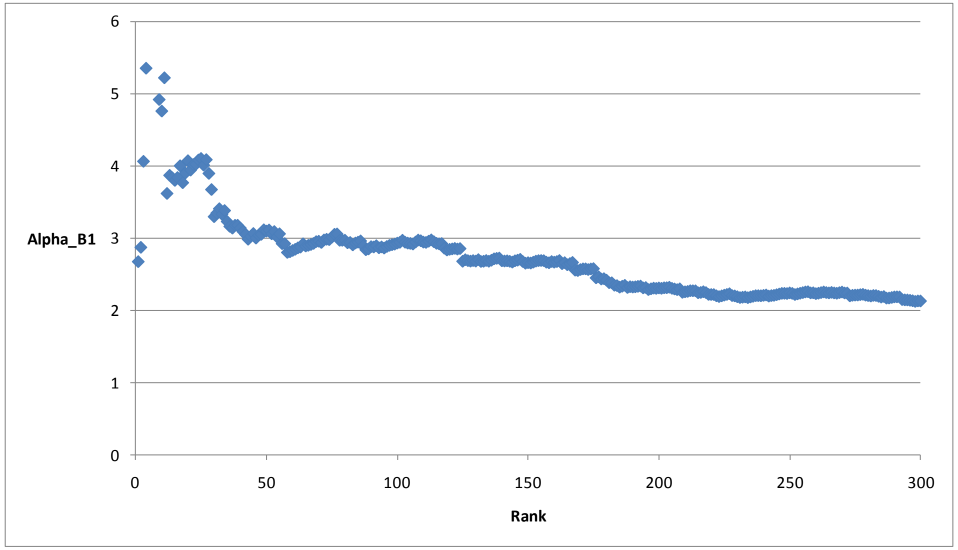
8.6.1 1987-1996



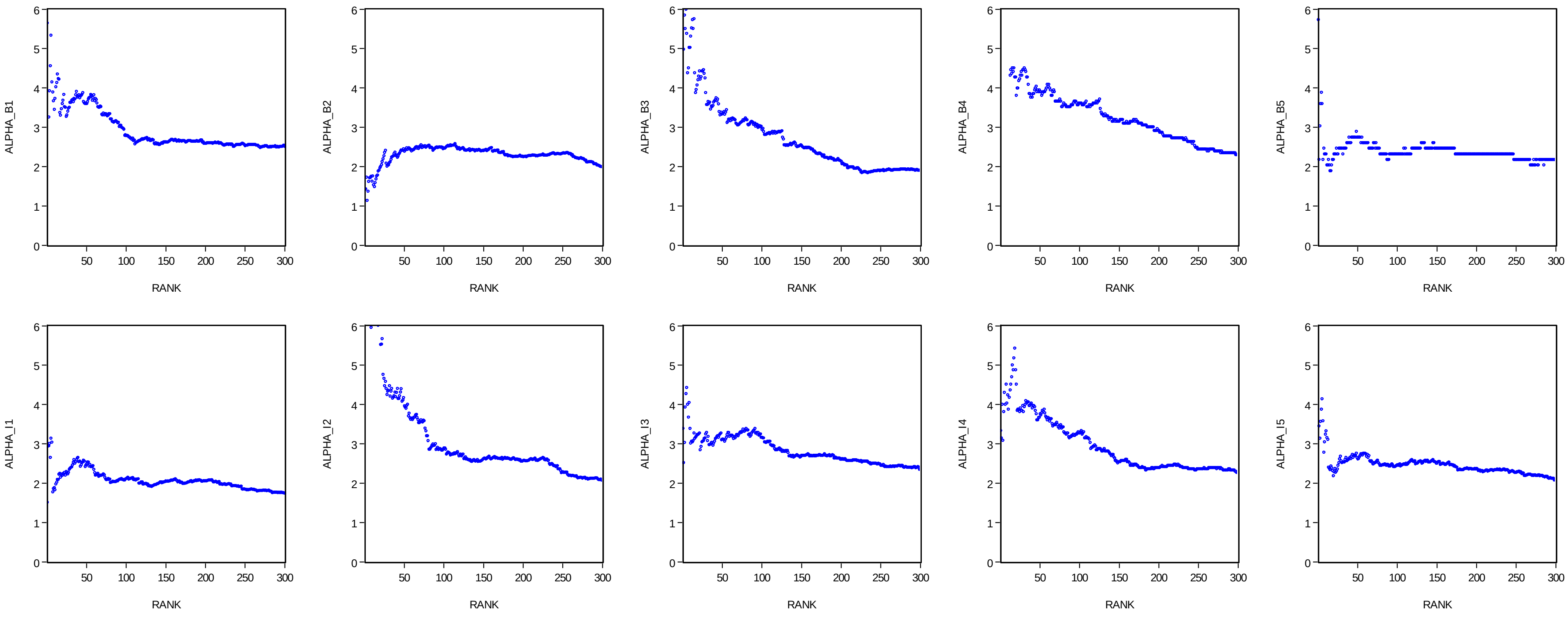
8.6.2 1997-2010*



* B1's Hill plot is clearly of an unexpected shape. Therefore, checks were run. The Eviews programme *02_generate_alphas_sorting.ascending.prg* was deemed to be sound as the plots' underlying series of alphas and higher order statistics for each of the banks were identical under Eviews and Excel. Only in the case of bank 1 (Danske Bank) did the plot differ from that generated in Excel. Therefore the Excel generated Hill plot for bank 1 is shown herenext.
In addition, the Hill plot for bank 5 was identical as that generated by Excel but with the flat steeps seen being less pronounced.



8.6.3 1992-2003*

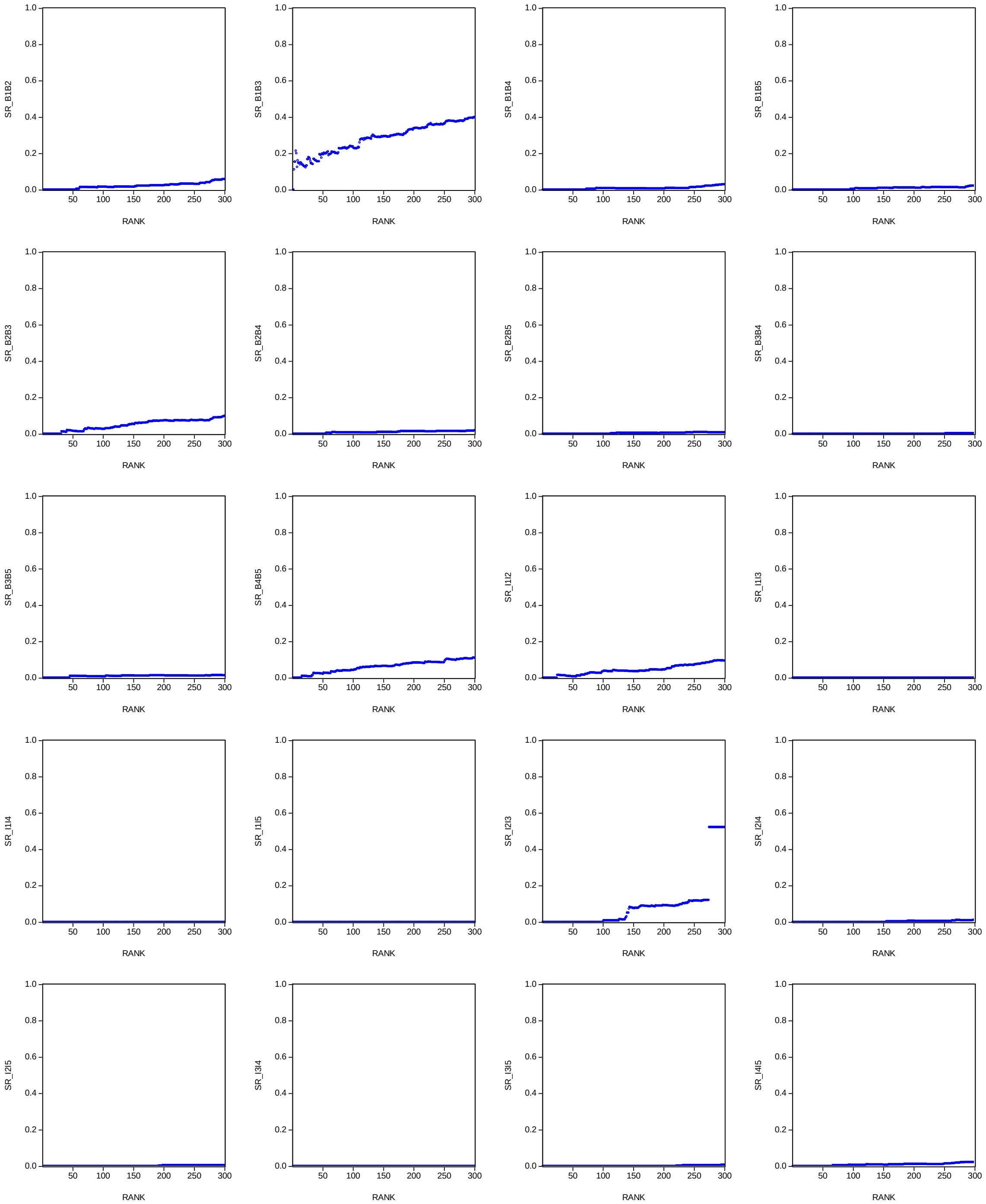


* As the Hill plot for bank 5 is of an unexpected shape, checks were run. The plot's underlying series for alphas and hiher order statistics were identical using the Eviews programme *02_generate_alphas_sorting.ascending.prg* and Excel. The resulting Hill plot generated under Excel has the same shape as the one generated under Eviews but has less pronounced flat steps than the Eviews one.

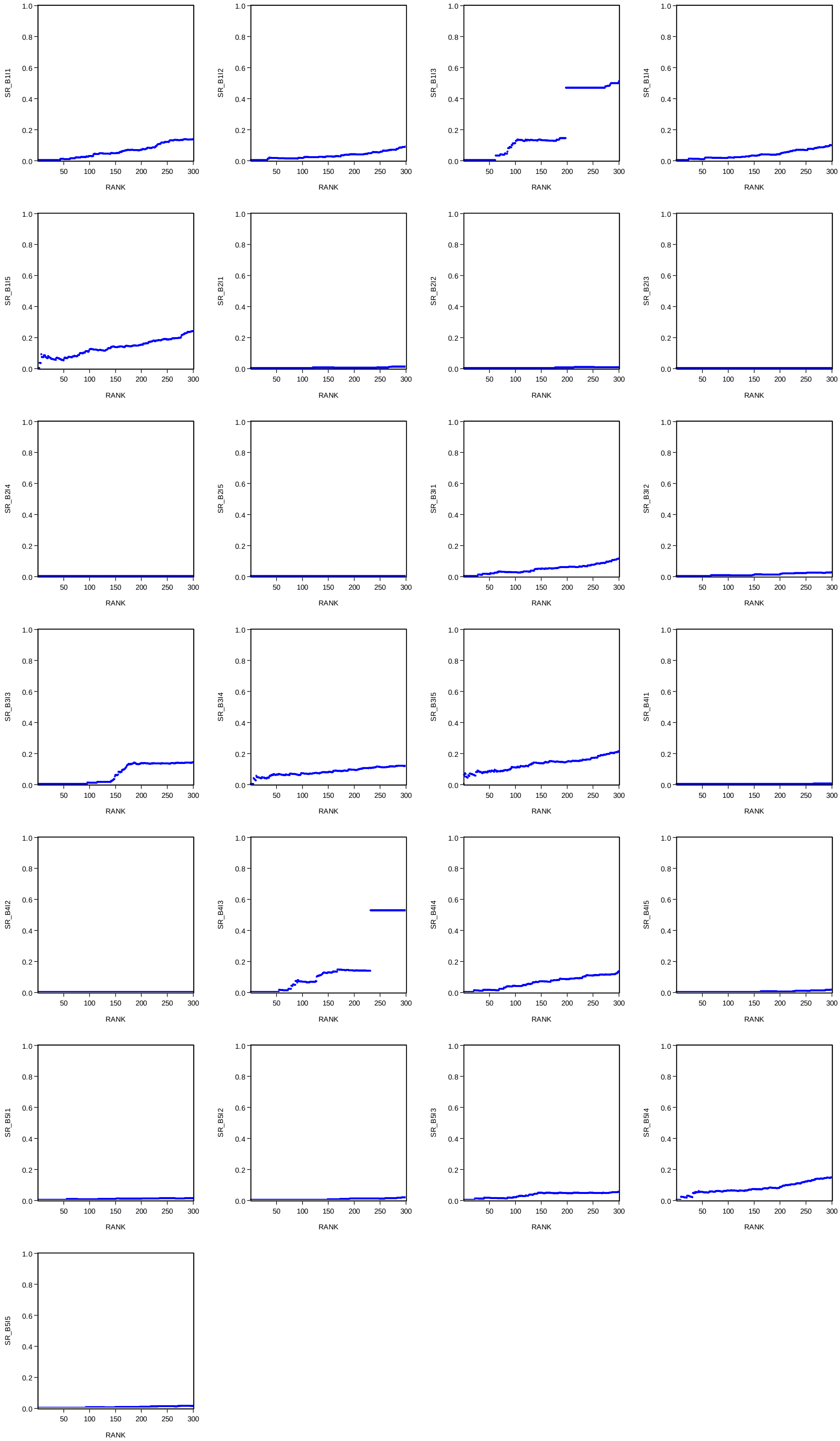
8.7 Systemic risk vs. higher order statistics plots

This section contains the $\widehat{SR(k)} - 1$ vs. higher order statistics plots for all possible combinations of entities and for the real data. For the within sector samples, the names *SR_B1B2* refers to the systemic risk between bank 1 and 2 and *SR_I1I2* refers to systemic risk between insurer 1 and 2. And across sectors, the name *SR_B1I1* refers to the systemic risk between bank 1 and insurer 1. Ranks are equivalent to the higher order statistics. For a list of the bank and insurer names in each sample period, see tables 9 and 10 on section 8.1.3.

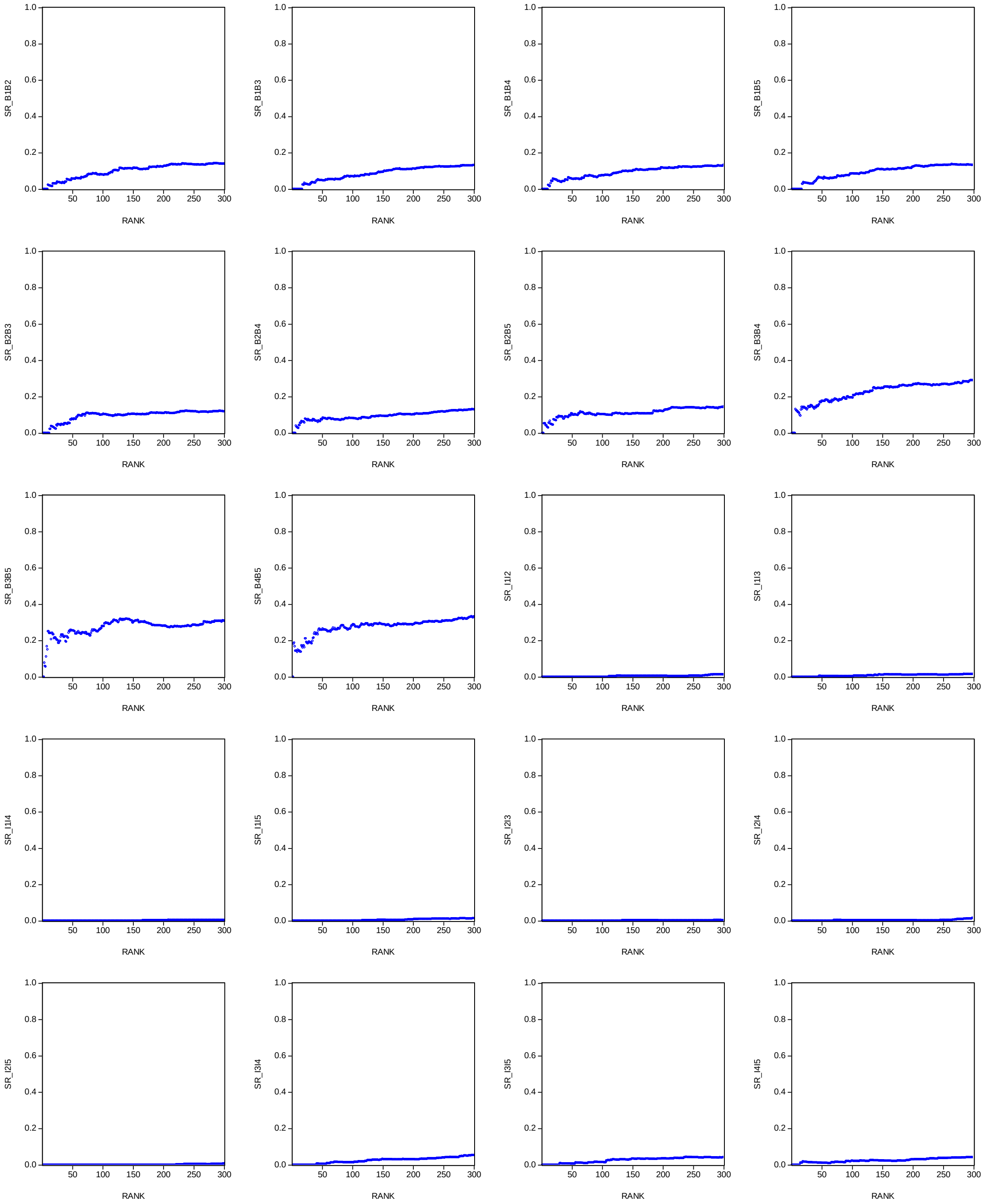
8.7.1 1987-1996 Within sector systemic risk



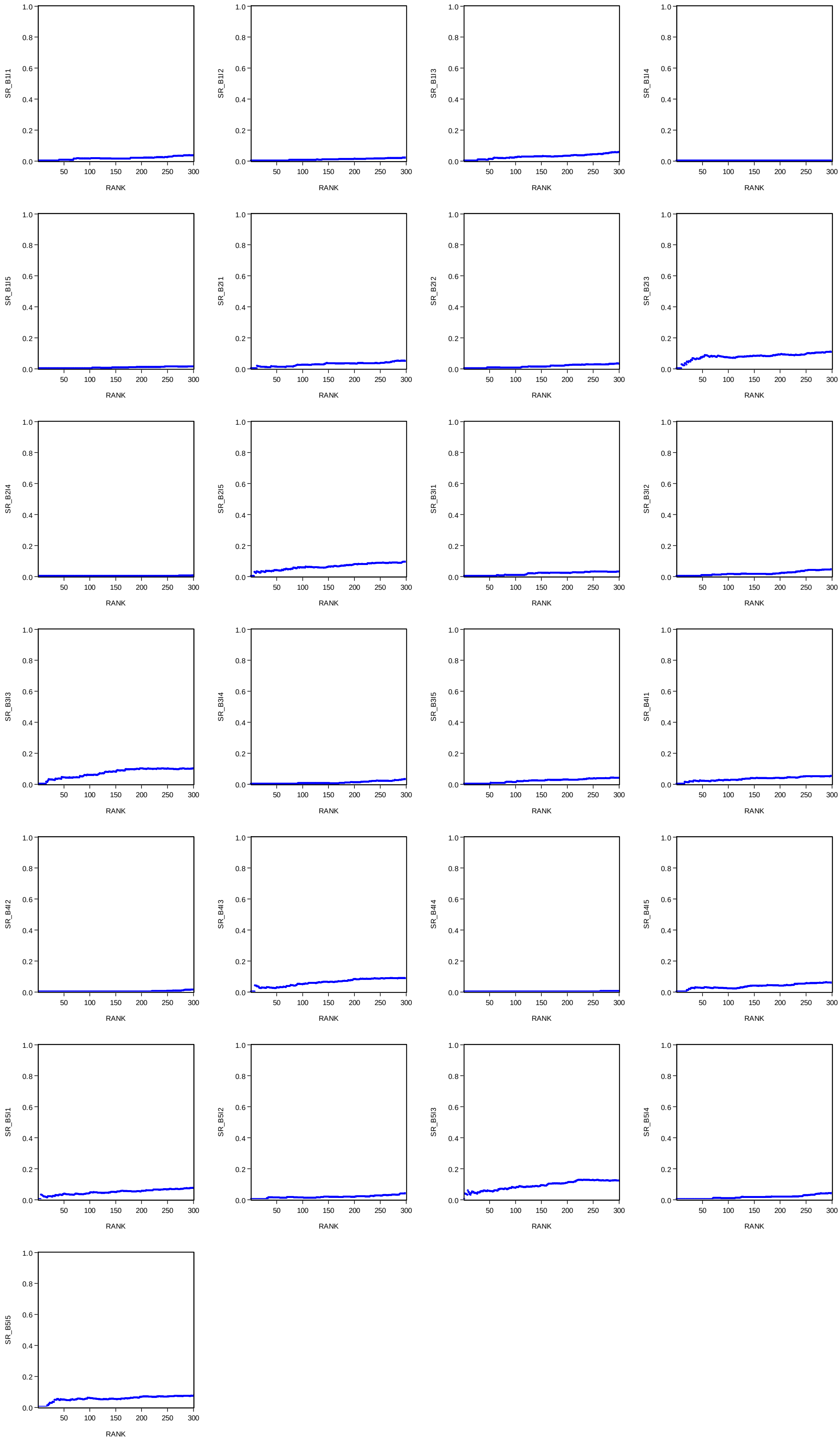
8.7.2 1987-1996 Cross sector systemic risk



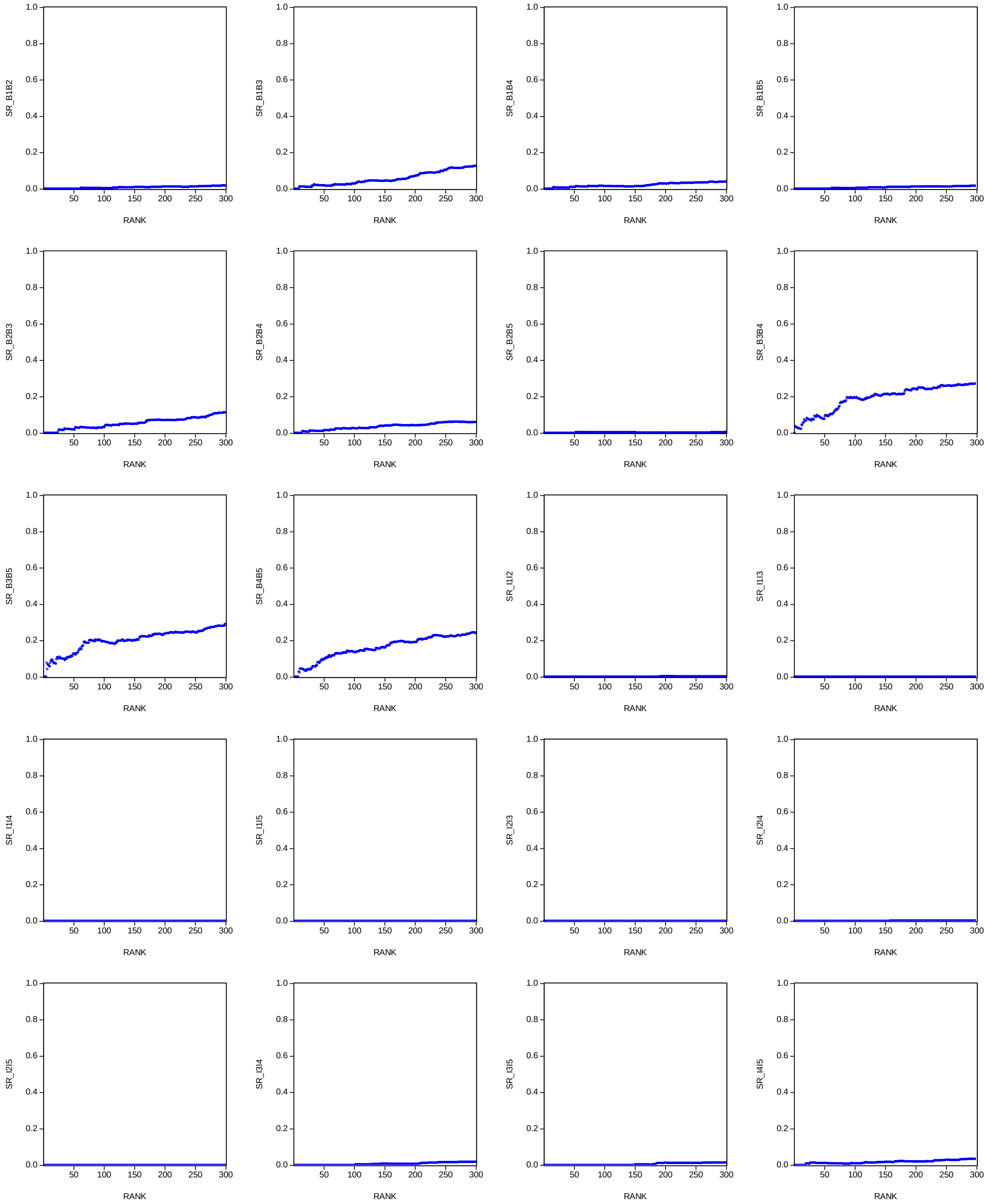
8.7.3 1997-2010 Within sector systemic risk



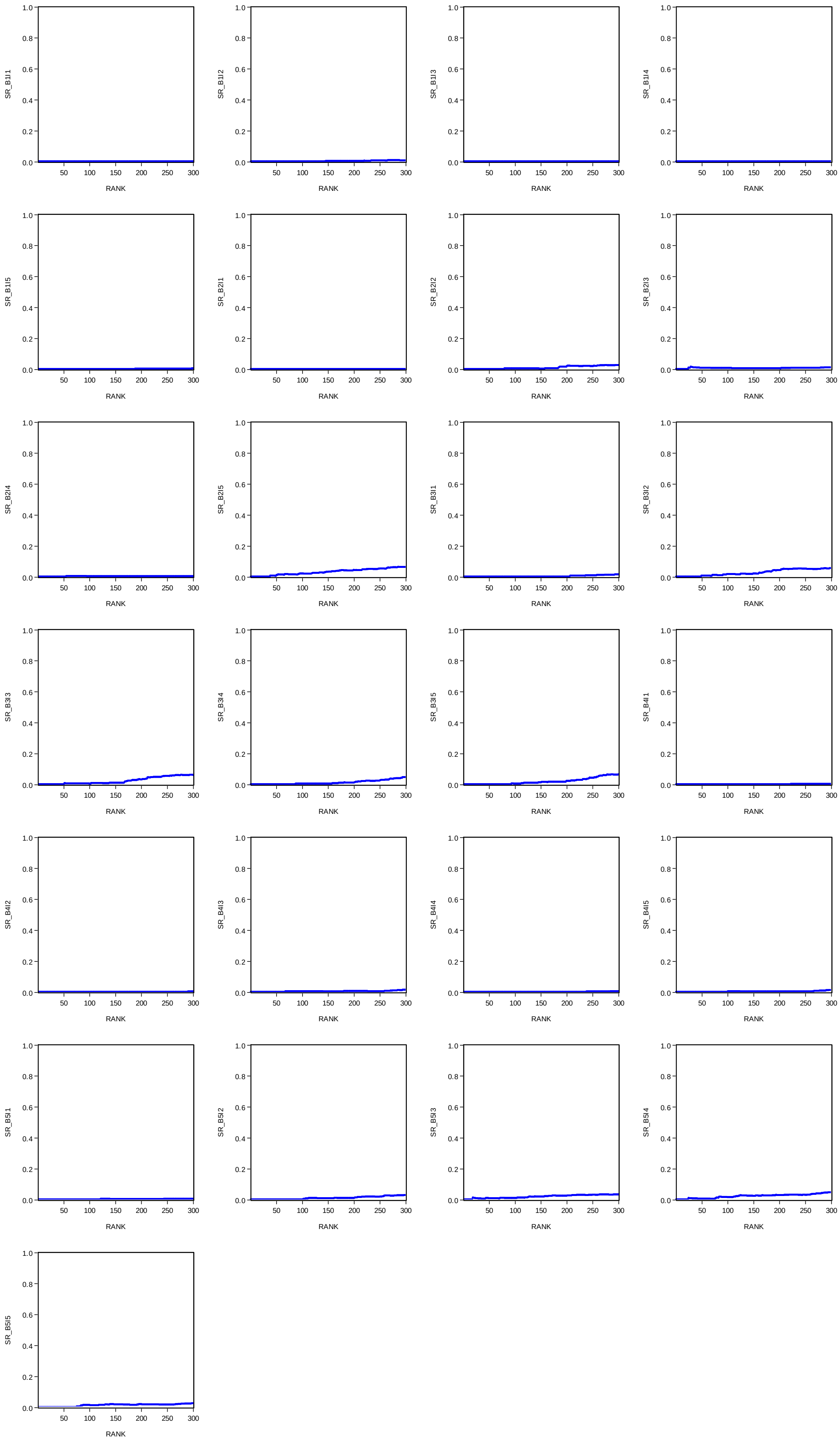
8.7.4 1997-2010 Cross sector systemic risk



8.7.5 1992-2003 Within sector systemic risk



8.7.6 1992-2003 Cross sector systemic risk



8.8 Replicate results guide

The programme files are available from the author at from the *data.zip* file available at the following website: http://www.nisolutions.nl/thesis/data.zip. Please allow for some time for the download to finish. If replicating the study please follow the guidelines below.

Step 1. Save the items under each period folder on the same directory. The period folders include all programme files (with the prg extension) and the work files (with the wf1 extension) necessary for the observation period.

Step 2. Open workfile *1987-1996_empty.wf1*, which contains the raw data, and run programmes with names starting with 01 to12. All programme files must be run from the 'untitled' workfile page. When running the programme file starting with 02, do remember to select 'maximum errors before halting' to 11. This is to be able to create NAs (non-available observations) out of zeros. These zeros are the result individual returns of zero which are located in the middle of a return distribution. For the Hill estimator exercise I take the natural logarithm of absolute returns. By allowing errors in this way, NAs are created and the programme continues.

Step 3. For the other periods do the same. Go to the relevant period folder and repeat steps 1 and 2.

On systemic risk estimate generation

Programmes which generate the systemic risk estimate, equation (2) can take anything between 2 to 3 minutes to run. These programmes allow the entering of a chosen threshold level (at the moment this is set to 0.036). This can be done by at the top of the programme, pay attention to comment to that effect. The programmes in question are:

- 3 and 4 for the raw data and within and cross sectors respectively.
- 6 and 8 for the bivariate normal distributed data and within and cross sectors respectively.
- 10 and 12 for the student-t distributed data and within and cross sectors respectively.

On systemic student-t random variable generation

Programmes 9 and 11 generate student-t distributed variables for within and across sectors respectively. Here the selected degrees of freedom need to be inserted (currently set to 3). See comment on programme to this effect.

8.9 Programme acronyms

To ease understanding and replication of results, here follows a list of the most important names used in the programme files.

Real data

Name	Meaning
graph_r_b1	line graph of bank 1
p_b1	RI data for banks
p_i1	RI data for insurers
r_b1	return of bank 1
r_i1	return of insurer 1
reg_b1b2	OLS regression of returns of bank 1 and bank 2
reg_b1i1	OLS regression of returns of bank 1 and insurer 1
scatter_b1b2	scatter plot of returns of bank 1 and bank 2
scatters_banks	group of scatter plots of bank combinations
scatters_cross	group of scatter plots of bank-insurer combinations
scatters_ins	group of scatter plots of insurer combinations
ss_banks	summary statistics for banks
ss_ins	summary statistics for insurers

Tail index

Name	Meaning
alpha_b1	tail index series for bank 1
cum_r_b1	cumulative sum of returns for bank 1, sorted ascending
hillplot_b1	tail index vs. higher order statistics plot for bank 1
ln_sa_r_b1	the natural logarithm of absolute values of sorted returns for bank 1
rank	rank series of higher order statistics
sa_r_b1	bank 1 returns sorted ascending

Systemic risk, real data

Name	Meaning
max_b1b2	maximum series of returns of bank 1 and bank 2
min_b1b2	minimum series of returns of bank 1 and bank 2
min_b1i1	minimum series of returns of bank 1 and insurer 1
sr_b1b2	series of systemic risk for banks 1 and bank 2
sr_b1b2_g	plot of systemic risk vs. higher order statistic for banks 1 and 2
threshold_b1b2	threshold series for bank 1 and bank 2 which is made up of the mean of the minimum and maximum series

Systemic risk, normal and student-t distributions

Name	Meaning
graph_n_b1i1	scatter plot of normal distributed returns of bank 1 and insurer 1**
graph_o_b1i1	scatter plot real returns of bank 1 and insurer 1
max_rn_b1i1	maximum series of normal distributed returns of bank 1 and insurer 1*
mean_rn_b1i1	series of mean normal distributed returns of bank 1 and insurer 1*
min_rn_b1i1	minimum series of normal distributed returns of bank 1 and insurer 1*
reg_rn_b1i1	OLS regression of normal distributed returns of bank 1 and insurer 1*
sr_rn_b1i1	series of systemic risk for bank 1 and insurer 1*
sr_rn_b1i1_g	plot of systemic risk vs. higher order statistic for bank 1 and insurer 1*

Systemic risk,
normal and student-t distributions (continued)

Name	Meaning
sr_rn_banks	group of systemic risk vs. higher order statistics for all bank combinations*
sr_rn_banks	group of systemic risk vs. higher order statistics plots for all insurer combinations*
sr_rn_cross	group of systemic risk vs. higher order statistics plots for all bank-insurer combinations
threshold_rn_b1i1	threshold series of normal distributed returns of bank 1 and insurer 2 which is made up of the mean of the minimum and maximum series*

* For student-t distributed variables, *_rn_* is replaced by *_rt_*

** For student-t distributed variables, *_n_* is replaced by *_t_*