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Measuring systemic risk in the Nordic countries

An application of CoVaR

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Abstract

Spillover effects and systemic risk contribution of institutions, as measured by their CoVaR and ΔCoVaR respectively, is one way of assessing risk both for an institution in isolation, as well as for regulators and the economy as a whole. CoVaR is the q%-VaR of an institution conditional on another institution already being at its q%-VaR level, whereas ΔCoVaR measures each institution's marginal risk contribution. This essay applies the CoVaR methodology proposed by Adrian and Brunnermeier (2011) on the Nordic stock market (OMX Nordic 40 Index) in order to measure systemic risk contribution of 36 firms on this market, during the period January 2002 to March 2014. Publicly available stock market data is used to estimate abovementioned measures by applying quantile regression. The results, which are aggregated at sector level, suggest that systemic risk contribution is higher during times of financial distress and sectors generally show a similar pattern in how risky they are over time. VaR is further not positively correlated with CoVaR, i.e. even if a sector is considered risky in isolation as measured by its VaR, it is not necessarily the case that it spills over this risk to other sectors/institutions. However, there are some sectors that contribute more to systemic risk than they are risky in isolation, as measured by their ΔCoVaR and VaR. Sectors contributing the most to Nordic systemic risk are Forestry and Construction, as well as the European stock market as measured by the EuroStoxx50 Index. The banks included in the OMX Nordic 40 Index are also examined in a separate case study, finding Swedbank the most risky and Nordea the least risky in isolation, but the other way around when measuring risk contribution (ΔCoVaR) of these two banks, to other banks.

Key words: systemic risk, VaR, spillover effects, CoVaR, quantile regression

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1 Introduction

Globalisation, increased integration and innovation in the financial and corporate markets have been the key drivers towards creating a globally intertwined financial system. Creating many benefits for the institutions involved, as well as for the real economy as a whole, financial advancement also comes at a cost. New channels of shock transmission arise due to the interconnectedness of institutions, and as we have observed during the recent global financial and Eurozone crises, externalities in the form of spillover effects are rules rather than exceptions.

Spillover effects are negative externalities arising from the integration of firms' financial activities. If mapped properly, they can be used to identify to what extent firms are linked and how they contribute to the probability of the entire financial system to collapse, i.e. how they contribute to systemic risk. Systemic risk is rarely brought up in typical finance textbooks and there is no unanimous definition of it. Instead, a lot of focus is put on market and/or credit risk where assets, firms or other entities are examined in isolation. So far, financial regulation such as Basel I and II has taken this stand-alone, micro prudential, approach in regulating the financial markets. As opposed to a macro prudential approach, which is being considered in Basel III, a micro prudential approach focuses on idiosyncratic risks of institutions rather than taking into account the risks that arise due to interaction between institutions. Hence, systemic risk is gaining the attention it needs by the inclusion of macro prudential parameters in financial legislation.

When discussing financial markets, one usually thinks of banks and other institutions associated with finance and financial activity. This is also the case when considering what research has been performed on systemic risk; financial institutions are considered being most risky and systemically important. Clearly, it is important to monitor, regulate and evaluate financial institutions but another growing perspective of systemic risk considers evaluating firms that on the one hand rely on credit from financial institutions, and on the other also create value for them. This essay does not specifically focus on the financial market per se, but instead considers the different firms and sectors that form the Nordic stock market, OMX Nordic 40 Index, and examines their contribution to Nordic systemic risk. As a case study, the banks included in the OMX Nordic 40 Index are also examined within the same framework. Systemic risk contribution is examined through the estimation of CoVaR, first presented by Adrian and Brunnermeier in 2011.

It is important to analyse the interconnection of institutions and to what extent these institutions, or sectors, are contributing to the over all systemic risk in order to maintain a well functioning risk management system and mitigate spillover effects. Regulating and monitoring systemic risk is not only important for the real

economy but also among corporate institutions that wish to minimise their risk exposure.

The study by Adrian and Brunnermeier (2011), CoVaR, serves as a foundation for this essay and the results obtained here are to a large extent based on replicating this study. CoVaR is a risk measure developed in response to VaR being an insufficient measure and that takes into account that there might exist different linkages between institutions having an impact on institution risk and performance in isolation. As far as the author is concerned, systemic risk contribution of Nordic firms has not yet been evaluated with the CoVaR methodology.

The aim of this essay is to examine systemically important firms on the Nordic stock market, as represented by the OMX Nordic 40 stock index. This is accomplished by applying the CoVaR methodology by Adrian and Brunnermeier (2011) to calculate each firm's systemic risk contribution on a sector basis. As a special case study, banks in particular are also examined in order to identify their risk linkages. The remainder of this essay is structured as follows; next follows a more detailed description of the problem formulation and the idea examined. Third, we assess existing literature on the topic of systemic risk and systemic risk contribution. Fourth, a brief theoretical framework is proposed where different risk measures are explained intuitively and formally. In chapter 5 we present the CoVaR estimation methodology and distinguish between a conditional and unconditional way of estimating CoVaR. The data is presented in chapter 6 and we find the empirical results in chapter 7, following a case study in chapter 8. The essay concludes with a summary including the main conclusions.

2 Problem formulation

The purpose of this essay is to quantify the level of systemic risk contribution in the Nordic stock market by identifying spillover effects of firms and sectors in this market using Adrian and Brunnermeier's CoVaR methodology. More specifically, the results of this essay attempt to answer the following questions:

Which sectors have the highest CoVaR?
Which sectors have the highest ΔCoVaR?

The first question is necessary to assess in order for the second question to be answered, however this essay focuses on the results of the second question. Both questions are nonetheless important. The first question deals with estimating spillover effects of firms onto the financial system, by means of CoVaR. That is, estimating the 1%-VaR of the Nordic stock market conditional on a firm already being at it's 1%-VaR level. The ΔCoVaR enables estimation of each firm's marginal contribution to Nordic systemic risk by taking the above estimated 1%-

CoVaR minus the 50%-CoVaR (50%-CoVaR is the 1%-VaR of the Nordic system conditional on a firm in the system being at it's 50%-VaR level). By calculating ΔCoVaR we are able to answer questions such as which firms are most at risk if a financial crisis should occur and which firms contribute the most to systemic risk on the Nordic stock market. The CoVaR and ΔCoVaR analyses serve as good tools both for the firm in isolation in terms of improving their risk management functions, as well as being an informative tool of a firm's sensitivity and relative standing in the corporate environment should negative shocks occur in the economy.

3 Previous research

According to Borri et al. (2012) literature on systemic risk contribution can be divided into two parts; network analysis and micro-evidence. Network analysis is concerned with the joint loss distribution of all market participants, whereas the micro-evidence approach focuses on the marginal contributions of individual institutions (López-Espinosa et al. (2012)). The focus in this essay, as well as the focus of the main paper on which this essay is based (Adrian and Brunnermeier (2011)), takes a micro-evidence approach in estimating systemic risk contribution and hence focus will be put on such studies in this section. For the interested reader, Hautsch (2012), Markose et al. (2010), Martinez-Jaramillo et al. (2010) and Cont et al. (2009) are examples of network analysis approaches on the topic.

There are several measures when it comes to assessing systemic risk within the micro-evidence based approach. One of them is CoVaR, developed by Adrian and Brunnermeier (2011) in their study with the same name. The authors propose a measure of systemic risk, which they denote CoVaR, with the prefix co standing for *conditional, contagion* or *comovement*, emphasizing the systemic nature of their risk measure. They define CoVaR as the VaR of a financial system j conditional on different institutions i being under distress, where VaR is the maximum loss that can occur with a specified probability during a specified time period and 'distress' is defined as an institution being at its 1%-VaR level.[1]

Further, the marginal contribution of each institution to overall systemic risk is defined as CoVaR conditional on the institution i being under distress (at its 1%-VaR level) *minus* the CoVaR conditional on the institution i being in its median state (at its 50%-VaR level). As we will investigate in depth in further sections, Adrian and Brunnermeier (2011) define systemic risk contribution, ΔCoVaR of each institution i as follows

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i = VaR_q^i} - CoVaR_{\mathrm{q}}^{j|X^i = \mathrm{VaR}^i_{Median}}$$

[1] If the terminology seems unclear at the time being, there is a very detailed explanation of VaR, CoVaR, other risk measures and estimation procedures in the theory and methodology sections of this essay.

with q being 1% in the first term and 50% in the second term on the right hand side of the equation. Estimations are carried out with quantile regression.[2]

The objective of their paper is twofold; they first propose a measure for systemic risk as outlined above, and secondly they outline a method called *forward* $\Delta CoVaR$ which is based on current institutional characteristics such as leverage, maturity mismatch and size, in order to predict firms' expected future contribution to systemic risk.

CoVaR (and therefore ΔCoVaR) is estimated both conditionally and unconditionally, for 1226 financial institutions including banks and thrifts, investment banks, insurance companies and government-sponsored enterprises (GSEs) in the US during the period 1986Q1-2010Q4. The unconditional estimation yields a CoVaR that is constant over time whereas the conditional estimation models CoVaR as a function of macro variables that are assumed to capture the evolution of tail risk over time, beyond that resulting from firms' asset returns and spillover effects. The additional macro variables include the slope of the US yield curve, the aggregate credit spread and the implied volatility VIX, serving as proxies for short-term liquidity risk, business cycle and investor sentiment. Forward ΔCoVaR is a forward looking measure of marginal systemic risk contribution of institutions constructed as regressing ΔCoVaR on different firm characteristics such as leverage, maturity mismatch, market-to-book value, size and equity return volatility. The authors conclude that characteristics such as higher leverage, more maturity mismatch and large size are contributing to a larger systemic risk contribution at both 1 % and 5 % levels. (Adrian and Brunnermeier (2011)).

An important conclusion drawn from the study of Adrian and Brunnermeier (2011) is that there is a very loose link between an entity's VaR and its contribution to systemic risk. This is a sign that financial regulation should not solely be based on VaR measures, but should rather take into account existing linkages among entities, when protecting against and managing systemic risk. For a more comprehensive presentation of the results from Adrian and Brunnermeier (2011), see Adrian and Brunnermeier (2011).

Different attempts to apply Adrian and Brunnermeier's CoVaR methodology have been made since its publication in 2011. For example, Chan-Lau (2008), Wong and Fong (2011), Roengpitya and Rungcharoenkitkul (2011), Borri et al. (2012), Arias et al. (2010) and Espinosa et al. (2012) have all, more or less, applied the CoVaR methodology in their research.

[2] Ibid

In the paper *Default Risk Codependence in the Global Financial System: Was the Bear Stearns Bailout Justified?*, Chan-Lau (2008) assesses the default risk codependence among 25 financial institutions in Europe, Japan and the US using quantile regressions and the idea of the CoVaR methodology. Risk codependence is here defined as the default risk of one institution conditional on the default risk of another institution post the correction for the effect of a number of observable fundamental and technical factors such as for example the slope of the US yield curve, excess stock market return, Libor spread and the implied volatility index VIX. Estimation is performed on publicly available daily market data on the 25 financial institutions, covering a period from July 2003 to September 2008. Chan-Lau analyses risk codependence by calculating a risk codependence coefficient and further examines how it varies at different levels of risk (quantiles). Quantile regression, as we will see in further sections, is nothing more than an optimisation problem and the following objective function is minimised in the study in order to solve for the risk codependence coefficient β at different quantiles τ. [3]

$$\min_{\beta} \sum_{i}^{N} \rho_{\tau} \left(Risk_i - \sum_{k}^{K} \beta_{k,\tau} R_k - \beta_{j,\tau} Risk_j \right)$$

The relevance of the above problem is to asses how the risk of institution i is affected by the risk of institution j, controlling for K risk factors R_k where the risk codependence between two institutions is captured by the parameters in the vector $\beta_{j,\tau}$. After having obtained risk codependence mappings the author also quantifies risk codependence between institutions in terms of the conditional codependence function for a specific quantile, measuring the percentage increase in the unconditional risk of firm (or financial system) i, as first proposed in Adrian and Brunnermeier (2008), but with somewhat different notation.

$$CoRisk_{ij}(\tau) \left(in\ percent \right) = 100 \times \left(\frac{(Risk_i(\tau) \,\big|\, Risk_j(\tau), R_k)}{Risk_i(\tau)} - 1 \right)$$

The results indicate that there exists an upward sloping pattern when it comes to the average risk codependence coefficient among the 25 financial institutions, i.e. risk codependence is stronger in times of financial distress (high quantiles). The author argues that despite the fact that there is no underlying structural model for the results, there is evidence of a transmission channel that exists between the economies beyond what could be explained by the exposure of common shocks in the economy. Chan-Lau's results also provide a description of the increase, in per cent, of the default risk of institution i when institution j is at it's 5%-VaR. Among the 25 financial institutions being evaluated during the time period, Bear Stearns and AIG were found to be most vulnerable to default risk spillovers, where the

[3] Again, a detailed description of the quantile regression methodology will come.

average conditional default risk increases 134 % and 187 % respectively, given a firm j being at its 5%-VaR level. (Chan-Lau (2008)).

Wong and Fong (2011), in *Analysing Interconnectivity Among Economies*, analyse the interconnectivity in terms of credit risk linkages using 11 Asian-Pacific economies' sovereign credit default swap spreads as the VaR variable. The CoVaR methodology of Adrian and Brunnermeier (2011) is also implemented here, but this time on sovereign CDS spreads of 11 Asian Pacific economies covering the period October 2004 to September 2009. Also here, quantile regression was implemented by relating economy i with economy j by the following model specification for q=1% where ΔX is the change in the CDS spread of economy i and where R_k is a vector of common macro variables

$$\Delta X^i = \beta_{0,q}^{i|j} + \beta_{1,q}^{i|j} \Delta X^j + \sum_{k=1}^{K} \gamma_{k,q}^{i|j} R_k + \varepsilon_q^{i|j}$$

Here $\beta_{0,q}^{i|j}$ represents idiosyncratic characteristics of economy i, and $\beta_{1,q}^{i|j}$ is the measure of risk dependency between economy i and the risk of economy j. CoVaR is formed in the following way

$$CoVaR_q^{i|j} = \widehat{\beta}_{0,q}^{i|j} + \widehat{\beta}_{1,q}^{i|j} VaR_q^j + \sum_{k=1}^{K} \hat{\gamma}_{k,q}^{i|j} R_k$$

The above equation allows estimating the maximum increase in the CDS spread that the economies could suffer. The authors conclude that the VaR of an Asian Pacific economy on average rises by 45% if another economy comes under financial distress, measured by the economy being at its 1%-VaR level. Indonesia and the Philippines are found to be most vulnerable in terms of suffering highest conditional risk, and Australia and New Zealand are found to be the least vulnerable. China and Korea are found to create the largest impact when it comes to risk spillover and affecting other Asian Pacific economies. Their results also show that risk measured by CoVaR is significantly higher than risk measured by standard VaR implying that there is evidence of a transmission channel among these economies. The authors' results, in accordance with previous studies, are concluded to be stronger in distress periods than in boom times. (Wong and Fong (2011)).

Arias et al. (2010) apply CoVaR to measure systemic market risk of Colombian financial institutions including pension funds, financial corporations, financial companies, financial cooperatives, brokerage firms, insurance companies and hedge funds. The data set includes weekly returns of Colombian treasury bonds of different duration and maturity together combined in what the authors call TES-portfolios, owned by the above-mentioned financial institutions. VaR and CoVaR of these portfolios belonging to each of the mentioned financial institutions is

calculated using quantile regression. They conclude that sectors with high levels of volatility, defined by sectors that often modify the composition and size of their investments in Colombian treasury bonds, contribute more to systemic risk. In this case, it was the sectors Financial Corporations and Financial Cooperatives that had the highest conditional risk codependence among financial sectors and therefore also contributing the most to systemic risk in the Colombian market. Commercial banks and brokerage firms had the lowest conditional risk codependence. A conclusion found in previous studies that risk codependence becomes larger during distress period is also confirmed by Arias et al. (2010).

Systemic Risk in the European Banking Sector by Borri et al. (2012) studies the systemic risk contribution of 223 European listed banks during the period 1999-2012. They follow Adrian and Brunnermeier's (2011) methodology and compute conditional VaR and ΔCoVaR on market valued asset returns, controlling for a set of macro variables that are considered important in determining asset values. These variables consist of the change of the DAX volatility index, a short and long term liquidity spread of Euribor 3M rate and German government bond yield, and 10 year and 3M German government bond yields, respectively. As previously mentioned, the macro variables account for the market specific information available to all entities involved on the market, as opposed to firm specific information that determines (extreme) asset value variation, and are included in the estimation in order to control for common events. The authors also examine what variables are considered as good predictors of systemic risk at the individual bank level, using ordinary OLS estimation technique. The authors find that ΔCoVaR is highly persistent and that size and leverage are two predictors of systemic risk contribution of banks. The variable Concentration, defined as banks having their headquarters in a more concentrated banking system, is also shown to be significantly different from zero, indicating that these banks contribute more to European wide systemic risk than other banks. (Borri et al. (2012)).

Roengpitya and Rungcharoenkitkul (2011) address systemic risk contribution in the Thai banking system using the CoVaR methodology. Risk contribution and financial linkages are quantified in a sample of Thai commercial banks covering the period 1996Q2 to 2009Q1, including the Asian crisis period. Daily stock market (equity price) data of 6 commercial banks in the Thai financial sector is used as their data sample. They also perform a panel data regression using bank balance sheet information in order to examine if ΔCoVaR in the Thai banking system can be explained by balance sheet characteristics. The authors chose to keep the analysed banks anonymous and denote them bank 1 to bank 6, where 1, 2, 3 and 5 are large commercial banks and 4 and 6 are considered medium sized banks. The first result implies the VaRs of the banks are positively correlated, indicating an underlying trend in VaRs. CoVaR estimations differ across banks, but bank 3 is perceived to contribute most to systemic risk, but is only ranked 4th in terms of

VaR. Likewise, bank 4, which has the most negative VaR, has smallest CoVaR. The authors conclude that significant (and varying) externalities may exist among banks and that this is something that has to be taken into consideration by regulators. The authors also analyse the correlation between size and systemic importance and find a coefficient of 0,26. The authors further investigate financial linkages between the banks in the sample by calculating firm-to-firm CoVaR and investigate possible explanatory characteristics that could explain the degree of financial linkage and spillover effects among the banks included. Size and interbank deposits are concluded to be two explanatory factors and asymmetries in ΔCoVaR are concluded to be present among the analysed banks. (Roengpitya and Rungcharoenkitkul (2011)).

Previous research confirms that CoVaR analysis is of importance and serves as a helpful tool in examining risk spillover and systemic risk contribution of different entities. The CoVaR methodology is not tied to, for example, a specific asset class, but could easily be applied to, for example, countries, which makes it a useful tool with broad application possibilities. What previous research also confirms is evidence of the existence of a shock transmission channel between entities after having controlled for common shocks as represented by macro (state) variables. This shock transmission is also proven to be stronger in times of distress, than in good times, pointing to the fact that asymmetries exist. There are many more studies on systemic risk contribution from a micro-evidential approach and again, the interested reader might find De Jonghe (2010), Segoviano and Goodhart (2009), Giglio (2010), López-Espinosa et al. (2012) or Lehar (2005) as interesting further reading suggestions.

4 Theoretical framework

4.1 What is systemic risk?

A very short and simple definition of systemic risk refers to the risk of an entire financial system to collapse. It is connected to the disruption of a financial system, having major negative consequences for the real economy, caused by breakdowns in all or parts of the system, at the same time. (De Bandt and Hartmann (1998), BIS, (1994)) There is no completely unanimous definition of systemic risk, as different definitions emphasize different aspects.

The Bank for International Settlements (BIS) defines systemic risk as

> *"the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties"* (BIS (1994), 64th Annual Review, page 177)

Kaufman and Scott (2003) propose that

> *"Systemic risk refers to the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by comovements (correlation) among most or all the parts"* (Kaufman and Scott (2003), page 371)

Rochet and Tirole (1997) refer systemic risk to

> *"… the propagation of an agent's economic distress to other agents linked to that agent through financial transactions"* (Rochet and Tirole (1996), page 733)

According to Kaufman and Scott (2003) three frequently occurring concepts of systemic risk appear in the literature. The first concept concerns the incidence of a big macro shock having large and simultaneous effects on the entire, or parts, of the system, rather than just affecting one or a few institutions. The second and third concepts are related to micro-level perceptions concerning the shock transmission and spillover effects arising between different institutions. This idea of systemic risk is often translated to chain reactions and domino effects in the system. (Kaufman and Scott (2003).

4.2 Measuring risk

Two of the most common risk measures in theory and practice are probably *Value-at-Risk (VaR)* and *Expected Shortfall (ES)*, defined as follows

$$VaR_\alpha\left(L\right) = \min\left\{l\colon \Pr(L > l) \leq 1-\alpha\right\}$$

$$ES_\alpha\left(L\right) = \frac{1}{1-\alpha}\int_\alpha^1 VaR_x\left(L\right)dx$$

VaR is defined as the minimum loss l such that the probability of a future loss L larger than loss l, is less than or equal to $1-\alpha$, or in case of a continuous loss distribution as $Pr(\mathrm{L} > \mathrm{VaR}_\alpha(L)) = 1-\alpha$. ES is often characterised as measuring losses "beyond VaR" in the sense that it evaluates the tail of large losses and calculates the average of the losses greater than VaR. In case of a continuous loss distribution, ES can also be defined more intuitively as $E\left[L\colon L > VaR_\alpha\ (L)\right]$. (Acerbi and Tasche (2002), JP Morgan (1996)).

Both measures are used extensively in practice, not least VaR, which is used in financial regulation when considering minimal capital requirements of banks as well as by commercial and investment banks when considering potential losses of portfolios.

4.3 Measuring systemic risk

VaR and ES normally take the approach of analysing the firm in isolation. Hence, they do not serve as proper risk measures when trying to quantify, for example, contribution to overall systemic risk, which is what is considered in this essay. Two measures that do are CoVaR and CoES, where CoVaR is the risk measure being considered in this essay and hence explained in more detail.

CoVaR is a risk measure first proposed by Adrian and Brunnermeier in 2011. It is defined as the VaR of an entity (e.g. firm, institution, country, portfolio) conditional on that another entity is in financial distress. Recalling that VaR (in terms of losses) of an entity is defined as

$$VaR_{\alpha}\left(L\right) = \min\left\{l\colon \Pr(L > l) \ \leq 1 - \boldsymbol{\alpha}\right\}$$

or more intuitively

$$Pr\left(X \leq VaR_q\right) = q$$

with X being the variable for which the VaR is defined (e.g. asset returns, CDS spreads; not necessarily losses), we can define CoVaR of entity j conditional on some event $\mathbb{C}(\mathrm{X}^{\mathrm{i}})$ of entity i in the following way

$$Pr\left(X^j \leq CoVaR_q^{j\left|\mathbb{C}\left(X^i\right)\right.} \middle| \mathbb{C}\left(X^i\right)\right) = q$$

Thus $\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j}|\mathrm{i}}$ is defined by the qth quantile of the conditional probability distribution above. The event $\mathbb{C}\left(\mathrm{X}^{\mathrm{i}}\right)$, causing entity i to be in financial distress, is normally defined as that entity having reached it's 1%-VaR level, i.e. $\mathrm{X}^{\mathrm{i}} = \mathrm{VaR}^{\mathrm{i}}_{\mathrm{q}=1\%}$, but, theoretically, it could be any negative event that is considered as being financially distressful. Further, an entity can be for example a single firm, many firms constituting a financial system, a country or another financial or non-financial institution or asset. Accordingly CoVaR is the VaR of some entity j, conditional on another entity i being at it's q %-VaR level. In terms of losses, CoVaR of entity j (with losses Y) conditional on entity i (with losses X) can be defined as

$$Pr\left(L^Y > CoVaR^{Y|X} \middle| L^X = VaR^X\right) = 1 - \alpha$$

CoVaR can also be used to analyse the risk contribution of one entity on another, or for example to analyse systemic risk contribution of a firm to a financial system

(or market), which is what is done in this essay. The interest lies in calculating $\Delta\mathrm{CoVaR}_{q}^{j|i}$ in the following way

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i = VaR_q^i} - CoVaR_q^{j|X^i = \mathrm{VaR}_{Median}^i}$$

Here, ΔCoVaR is calculated as the 1% CoVaR (i.e the 1% VaR of entity j conditional on entity i being on its 1%-VaR level) minus the 50%-CoVaR (i.e the 1% VaR of entity j conditional on entity i being in it's median state, i.e. on it's 50 %-VaR level). Adrian and Brunnermeier (2011) suggest calling $\Delta\mathrm{CoVaR}_{q}^{j|i}$, where i is defined as being the financial system, as *"exposure CoVaR"* due to the fact that it measures the sensitivity of an individual institution towards systemic (system wide) financial events. The $\Delta\mathrm{CoVaR}_{q}^{j|i}$ measure is interesting because it can help identifying the most critical firms in terms of being most vulnerable during financial crises. (Adrian and Brunnermeier, (2011))

Like CoVaR's similarity with VaR, we can now define CoES^{i} as

$$CoES_{\alpha,\beta}\left(Y, X\right) = \frac{1}{1-\beta}\int_{\beta}^{1} CoVaR^{Y|X} dt$$

defining Y and X as losses of entity Y (normally the financial system) and X (the firm within the chosen financial system) respectively, and α and β as significant levels (normally 1% or 5%) (Adrian and Brunnermeier (2011)).

4.4 Related systemic risk measures

Apart from CoVaR and CoES a number of other related systemic risk measures have evolved as a response to different shortcomings or modifications of the above-mentioned measures.

Huang, Zhou and Zhu (2010) adopt a systemic risk indicator that is measured by the price of insurance against systemic financial distress and assesses marginal system risk contributions of 19 bank holding companies. The systemic risk indicator is here defined as the insurance premium that protects against distressed losses of a hypothetical debt portfolio consisting of the total liabilities of all banks. The systemic risk, or also termed *Distress Insurance Premium (DIP),* of the banking system is then given by the risk-neutral expectation of the portfolio loss exceeding a certain threshold level.

$$DIP = E^Q\left[L \middle| L \geq L_{min}\right]$$

L_{min} denotes the minimum loss threshold and L_i is denoted by the loss of bank *i*'s liability, with $\sum_{i=1}^{N} L_i = L$ being the total loss of the portfolio including all bank's liabilities. Systemically important banks and marginal systemic risk contribution of each bank *i*, can now be obtained by the partial derivative of the DIP with respect to bank *i*

$$\frac{\partial DIP}{\partial L_i} \equiv E^Q \left[L_i \middle| L \geq L_{min} \right]$$

Another related systemic risk measure that has its origins in VaR and ES is *Systemic Expected Shortfall (SES)* and *Marginal Expected Shortfall (MES),* as proposed by Acharya et al. (2010) in their paper named *Measuring Systemic Risk.* Without laying out detailed specifics, the authors propose a measure of systemic risk, systemic expected shortfall (SES), where each institution's systemic risk contribution can be measured by its propensity to be undercapitalised when the system is undercapitalised, which is an increasing function of the firm's volatility, leverage and tail-dependence. The authors suggest that institutions be "taxed" according to their SES in order to internalise the externality of their marginal contribution to systemic risk.

Another risk measure, closely related to the DIP and the SES, is the Marginal Expected Shortfall (MES), also proposed by Acharya et al. (2010). The MES considers the expected loss of an entity conditional on the whole group of banks being under distress, i.e. it measures how entity *i*'s risk taking is affected by the risk taking of entity *j*.

$$MES_q^i \equiv E(L_i \middle| L \geq VaR_q)$$

Compared with the DIP, the MES differs in the sense that the extreme condition is characterised by a percentile (i.e. q%-VaR), whereas the DIP focuses on a given threshold loss of the portfolio. (Acharya et al. (2010))

Another way of quantifying systemic risk is by using *Shapley values.* The actual origin and application of Shapley values is in game theory, published in *A value for n-person games* by Shapley (1952). The game theoretic Shapley value methodology is applied in cooperative games where a player's Shapley value is his expected marginal contribution over all sets of combinations on the set of players in the game. As Cao (2013) explains, the methodology can be applied on the financial system where the Shapley value in that case is the systemic risk generated by the entities within the system. The idea of Shapley values is then to (efficiently) allocate total systemic risk to each institution in the system, according to the game theoretic solution concept. As the concept lies outside of the scope of this essay, I

encourage the interested reader to see Cao (2013), Tarashev, Borio and Tsatsaronis (2010) or, Shapley (1952) for the original work.

Hansen (2013) further divides systemic risk measurements in four different groups; *tail measures, contingent claims analysis, network models* and *dynamic stochastic macroeconomic model*s. Adrian and Brunnermeier's CoVaR methodology can be found in the first group that focuses on co-dependence in the tails of equity returns. Contingent claims analysis is based on option pricing theory where the value of firm assets can be assumed to follow an underlying stochastic process where equity is a call option on firm assets, and debt is the corresponding put option. Network models, as mentioned in the section of previous research, focuses on the interconnectedness of institutions. Dynamic stochastic macroeconomic models try to connect financial market disruption with macroeconomic forces (Hansen (2013)). The literature on systemic risk measures is, as demonstrated, large and wide, depending on what perspective one wants to capture. For a comprehensive overview of literature that addresses systemic risk see DeBandt and Hartmann (2000) or Bisias et al. (2012).

5 Methodology

This essay takes a statistical and econometric approach in obtaining the results and drawing the conclusions. Specifically, the method of *quantile regression* (QR) (Koenker and Bassett (1978)) is applied to implement the CoVaR methodology of Adrian and Brunnermeier (2011). QR is not the only means of estimation; a bivariate GARCH framework can also be used and will be demonstrated at the end of the methodology section.

5.1 Quantile regression

Quantile regression (QR), as first proposed by Koenker and Bassett (1978), is an econometric regression method that involves estimating the conditional median (or any quantile) of the variable in question, unlike OLS, which involves estimating the conditional mean. In this way QR is able to describe the relationship between variables at different points in the conditional distribution of the dependent variable.

QR is used due to its straightforward and simple estimation procedure and it is also easily available in all statistical software packages. Generally, QR is based on minimising the sum of residuals in absolute value, where the residuals are weighted asymmetrically through the quantile, depending on if they are positive or negative. As opposed to OLS, QR models the relationship between the independent variable(s) and the conditional quantiles of the dependent variable. The advantages of QR over OLS are that QR is more robust to outliers and non-normal residuals

than OLS, and it is also invariant to monotonic transformations, unlike the mean in OLS. (Brian and Noon, (2003))

Consider the following simple model that can be used to describe the method underlying QR

$$y_i = x_i{}'\beta_q + u_i$$

where β_q is the vector of unknown parameters associated with a particular quantile q, y is a vector of dependent variables, x is a vector of independent variables and u is a vector of residuals. Following the logic in OLS, the sum of residuals is minimised but unlike OLS, the residuals are not squared in a QR. The following optimisation problem is formed

$$\min_{\beta} \sum_{i}^{N} \rho_q\left(u_i\right) \ = \min_{\beta} \sum_{i}^{\mathrm{N}} \rho_q\left(y_i - x_i{}'\beta_q\right)$$

where $\rho_q\left(u_i\right)$ is a weighting function for quantile q given by. $u(q-1(u<0\ ))$. The weights are determined depending on if the residuals are positive or negative and can be interpreted as asymmetric penalties. A weight of *1-q* is given to negative residuals, i.e. if the fitted value underestimates the observed value, and a weight of q is given to positive residuals, i.e. if the fitted value overestimates the observed value. Taking above information into consideration, the objective function takes the following, expanded, form

$$\min_{\beta} Q\left(\beta_q\right)$$

where

$$Q\left(\beta_q\right) = \sum_{i=y_i \geq x_i{}'\beta_q}^{N} q\left|y_i - x_i{}'\beta_q\right| + \sum_{i=y_i \leq x_i{}'\beta_q}^{N} (1-q)\left|y_i - x_i{}'\beta_q\right|$$

Note that this solution will yield different values of the coefficient estimate β depending on what quantile q is chosen. In this way, QR is implemented by forming an optimisation problem. The QR estimator will be asymptotically normally distributed even though it does not require any initial distributional assumptions about the residuals. (Koenker and Hallock, (2001)).

In regular order, marginal effects are obtained by taking the derivative of the conditional quantile function with respect to the parameter of interest *j*.

$$\frac{\partial Q_q\left(y_i \middle| x_i\right)}{\partial x_j} = \beta_{qj}$$

where

$$Q_q\left(y_i \middle| x_i\right) = x_i{}'\beta_q$$

The interpretation of a quantile regression parameter β_{qj} should now be clear. β_{qj} estimates the change in a quantile q of the dependent variable, generated by a one-unit change in the independent variable. This technically summarises what the CoVaR methodology is about and, hopefully, complements the practical explanations demonstrated in the previous section.

5.2 Estimation of VaR, CoVaR and ΔCoVaR

As previously mentioned, CoVaR and ΔCoVaR can be estimated under a conditional or unconditional framework. The unconditional framework yields measures of VaR, CoVaR and ΔCoVaR that are constant over time and it does not control for economy wide shocks that have an impact on the firms. It gives a static approach to systemic risk at a given point of time based on historical movements of stock returns only. The conditional approach for estimating the abovementioned risk measures tries to "refine" CoVaR by controlling for the abovementioned economy wide shocks in order to explain how firms' (extreme) returns affect other firms' (extreme) returns. In other words, the goal is to focus on idiosyncratic risk, rather than idiosyncratic and systematic risks together. Economy wide shocks are represented by several macro variables, which are included in the estimation procedure, and which are assumed to explain asset returns. These could be indicators of, for example, investor sentiment or the business cycle or simply returns of other markets. Conditional estimation of CoVaR can therefore be referred to as a dynamic approach, unlike the unconditional estimation approach which in a similar manner could be called a static approach.

To avoid confusion; the term CoVaR always includes two entities of some form. In this essay, when referring to CoVaR, these two entities are either the Nordic system (OMX Nordic 40=OMX) and some firm's stock *i*, or the Nordic system (1) and the European system (2), (EuroStoxx50=ES), if not otherwise stated. These are referred to as $\mathrm{CoVaR}^{\mathrm{OMX}|\mathrm{i}}$ and $\mathrm{CoVaR}^{\mathrm{OMX}|\mathrm{ES}}$ respectively, or only CoVaR if the information applies to both expressions.

5.2.1 Unconditional estimation of VaR, CoVaR and ΔCoVaR

CoVaR can be easily estimated using statistical software that applies the previously described technique of QR. To obtain $CoVaR^{\mathrm{OMX}|i}$, in the way we earlier defined it, we first have to obtain 1% and 50%-VaR of stock *i*, for i=1,2,…,37, which we do by simple historical simulation. Remembering the definition of VaR; since VaR_q^i is the quantile q of the returns of firm's stock *i*, we run a QR of firm *i*'s returns on a constant only, with q=1% and q=50% for median state VaR:

$$X_q^i = \alpha_q^i + \varepsilon_q^i \qquad (1)$$

$$VaR_q^i = \widehat{\alpha}_q^i \qquad (2)$$

Similarly for the system,

$$X_q^{system} = \alpha_q^{system} + \varepsilon_q^{system} \qquad (3)$$

$$VaR_q^{system} = \widehat{\alpha}_q^{system} \qquad (4)$$

To obtain the actual $CoVaR^{OMX|i}$, which we define as the 1% VaR of the system conditional on that a firm i is on its 1% VaR level, we (quantile) regress the system's returns on a constant and the returns of firm i:

$$X_q^{OMX,i} = \alpha_q^i + \beta_q^i X^i + \varepsilon_q^i \qquad (5)$$

We obtain the coefficients of α and β from the above regression, and use them together with the obtained VaR_q^i (equation 2) and construct $CoVaR^{OMX|i}$

$$CoVaR_q^{OMX|X^i=VaR_q^i} = VaR_q^{OMX}\Big|VaR_q^i = \widehat{\alpha}_q^i + \widehat{\beta}_q^i VaR_q^i \qquad (6)$$

and further construct ΔCoVaR

$$\Delta CoVaR_{q=1\%}^{OMX|i} = \widehat{\beta}_{q=1\%}^i \left(VaR_{q=1\%}^i - VaR_{q=50\%}^i \right) \qquad (7)$$

Similarly, to obtain $CoVaR^{\mathrm{OMX}|\mathrm{ES}}$, i.e the VaR of the Nordic OMX system conditional on the Eurostoxx50 (European market) being in financial distress and vice versa, we perform the same QR, but instead of regressing on firms' returns, we regress on the index (system) returns and use the estimated system VaRs to construct $CoVaR^{\mathrm{OMX}|\mathrm{ES}}$.

$$X_q^{OMX,ES} = \alpha_q^{ES} + \beta_q^{ES} X^{ES} + \varepsilon_q^{ES} \qquad (8)$$

$$CoVaR_q^{OMX|X^{ES}=VaR_q^{ES}} = VaR_q^{OMX}\Big|VaR_q^{ES} = \widehat{\alpha}_q^{ES} + \widehat{\beta}_q^{ES} VaR_q^{ES} \qquad (9)$$

$$X_q^{ES,OMX} = \alpha_q^{OMX} + \beta_q^{OMX} X^{OMX} + \varepsilon_q^{OMX} \qquad (10)$$

$$CoVaR_q^{ES|X^{OMX}=VaR_q^{OMX}} = VaR_q^{ES}\Big|VaR_q^{OMX} = \widehat{\alpha}_q^{OMX} + \widehat{\beta}_q^{OMX} VaR_q^{OMX} \qquad (11)$$

Finally, ΔCoVaR, i.e. how much the Nordic stock system contributes to European systemic risk and vice versa, is obtained by

$$\Delta CoVaR_{q=1\%}^{OMX|ES} = \widehat{\beta}_{q=1\%}^{ES}\left(VaR_{q=1\%}^{ES} - VaR_{q=50\%}^{ES}\right) \qquad (12)$$

and

$$\Delta CoVaR_{q=1\%}^{ES|OMX} = \widehat{\beta}_{q=1\%}^{OMX}\left(VaR_{q=1\%}^{OMX} - VaR_{q=50\%}^{OMX}\right) \qquad (13)$$

As specified in the above equations, regressions are run on all firms as well as for the two indices for quantiles 1% and 50%.

The regressions enable a construction of each firm's (static) systemic risk contribution to the Nordic stock market as proxied by the OMXNordic40 index, as well as the Nordic market's systemic risk contribution to European systemic risk, as proxied by the EuroStoxx50 index.

5.2.2 Conditional estimation of VaR, CoVaR and ΔCoVaR

In order to get a more refined estimation of CoVaR, the above estimation can also be applied including additional macro variables other than only stock returns, as accomplished above. These variables can represent, for example, the business cycle, investor sentiment or time variation of assets returns, or any other variables that are presumed to explain and affect stock returns. These variables should be interpreted as conditioning variables that intend to control for non-idiosyncratic, i.e. market specific, risks. The chosen macro variables will be motivated and presented in the data section that follows this part.

The following QR is run on a firm's stock's daily returns for quantile q=1% and q=50% for i=1,2…37. This to obtain time varying 1%-VaR and 50%-VaR series, conditioned on macro variables included in the vector M.

$$X_t^i(q) = \alpha_q^i + \beta_q^i M_t + \varepsilon_t^i \qquad (14)$$

With estimates of α and β parameters we can now form a conditional VaR series of firm (stock) i

$$VaR_t^i(q) = \widehat{\alpha}_q^i + \widehat{\beta}_q^i M_t \qquad (15)$$

For the system specific return, i.e. OMX Nordic 40 and EuroStoxx50 in this essay, we follow the same logic to obtain a time varying system VaR series

$$X_t^{sys}(q) = \alpha_q^{sys} + \beta_q^{sys} M_t + \varepsilon_t^{sys} \qquad (16)$$

$$VaR_t^{sys}(q) = \widehat{\alpha}_q^{sys} + \widehat{\beta}_q^{sys} M_t \tag{17}$$

where *sys* denotes the OMX Nordic 40 index and EuroStoxx50 Index as before.

For the estimation of CoVaR and ΔCoVaR we run the following regressions, also for q=1% and q=50%

$$X_t^{sys|i}(q) = \alpha_q^{sys|i} + \beta_{q,1}^{sys|i} X_t^i + \beta_{q,2}^{sys|i} M_t + \varepsilon_t^{sys|i} \tag{18}$$

$$CoVaR_t^i(q) = \widehat{\alpha}_0^{sys|i} + \widehat{\beta}_{q,1}^{sys|i} VaR_t^i(q) + \widehat{\beta}_{q,2}^{sys|i} M_t \tag{19}$$

where X_t^i are the returns of firm i. We finally calculate each firm's systemic risk contribution (ΔCoVaR) to the Nordic market (equation 20), as well as the Nordic market's marginal contribution to European systemic risk (equation 21) as follows

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i\left(q = 50\%\right) \tag{20}$$

$$\Delta CoVaR_t^{sys}(q) = CoVaR_t^{sys}(q) - CoVaR_t^{sys}\left(q = 50\%\right) \tag{21}$$

This way of estimating $\text{CoVaR}^{\text{OMX}|\text{i}}$ and $\text{CoVaR}^{\text{OMX}|\text{ES}}$ is denoted time varying conditional CoVaR by Adrian and Brunnermeier (2011). It takes into account the time varying nature of risk and conditions VaR on information available at time t, explaining the fact why we now have an index t in the equations as opposed to unconditional CoVaR estimation, which is a constant-over-time-approach.

5.2.3 CoVaR using GARCH models

The parameter estimates necessary for calculating CoVaR can also be solved by estimating a bivariate diagonal vech GARCH(1,1) model for each institution. Technically and practically harder, this method allows obtaining the time-varying covariance between institutions and the system through a Gaussian framework where CoVaR has a closed form expression. As part of robustness checks, Adrian and Brunnermeier (2011) performed their estimations using a bivariate GARCH framework and found that the results, as opposed to estimation with QR, did not differ significantly. Also, estimation with GARCH requires strong distributional assumptions that practically can be ignored using QR. With this in mind and following the rule of thumb of model parsimony, QR is concluded sufficient in estimating CoVaR in a, relatively, reliable way and serves as a motivation for why this technique was chosen also in this essay.

6 Data

The data used in this essay consists of macro and stock market data, all publicly available in either Datastream or on the Nasdaq OMX website. The stock market data constitutes the bulk of the data used in this essay. Daily adjusted closing prices of 36 firms' stocks, as listed on the OMX Nordic 40 index, as well as the index itself, representing the Nordic financial system, are collected for the period January 1st 2002 to March 31st 2014. All 40 stocks in the index are unfortunately not used due to missing data during the entire time period. The EuroStoxx50 index, representing the European stock market, is also collected during the same time period. Firm and index data is transformed according to

$$\frac{P_{i,t+1} - P_{i,t}}{P_{i,t}} = X_{i,t}$$

which yields the returns in per cent of the abovementioned data. Percentage returns are used due to their convenience, and due to prices being nominated in three different currencies. In this way, we are able to obtain a unit free measure of returns. Stock market data was chosen in this essay for the simple reason that it reflects many different types of risk that build up overall systemic risk. As we have seen, CDS data can, with advantage, also be used but it mainly captures credit risk and might be useful when considering for example credit risk linkages specifically.

The firms listed on the OMX Nordic 40 Index can be found in appendix 1 and below is a specification of the represented sectors:

Table 1 Specification of sectors represented in the OMX Nordic 40 Index (as of 2014.03)

	Sector	**#**
1	Transportation/shipping	1
2	Manufacturing	8
3	Health care	5
4	Automotive	2
5	Consumer products	5
6	Financials	7
7	Telecommunications	4
8	Utility	1
9	Construction	1
10	Forestry	2

When it comes to choosing what macro variables to include in the estimation of conditional CoVaR, one has to take into consideration what factors might affect the stock returns of Nordic firms. Even though each firm reacts to these macroeconomic factors differently, it makes sense to choose variables that the firms might have in common. With reference to Adrian and Brunnermeier (2011), and

also Chan-Lau (2008) the following macro variables were chosen to be included in the conditional CoVaR estimations in this essay

1. *Volatility of the Eurostoxx50 Index*
2. *Returns on the S&P500 index*
3. *Euribor 3 month interest rate*

The three chosen variables represent investor sentiment, trend and expectations, and a business cycle indicator, respectively. The volatility of the Eurostoxx50 index is expected to have a negative impact on CoVaR and ΔCoVaR, returns on S&P500 index are expected to have a positive impact and the change in the 3month Euribor interest rate can both have a negative and positive impact on the firm, depending on what industry the firm in question is in. To avoid problems of non-stationary data, the variables are expressed in first differences and further modified in the same way as the stock data.

7 Empirical results

To get a simple overview of the results, and for practical and space related purposes, all results are sector specific and will be presented in averages and semi-annual averages of the daily estimates, if not otherwise stated. Firm specific results and estimations can be found in Appendix 2. Sector specific results are constructed by taking the average of the firms included in the specific sector, as presented in the data section. To avoid confusion, the results will be structured as follows; first, descriptive statistics of the return and macro variables data will be presented. Second, unconditional estimation of VaR, CoVaR and ΔCoVaR will be presented. Since estimations are unconditional, these measures are constant over time and can be seen as snapshots of today based on returns information contained in the period 2002-2014. Third, conditional VaR, CoVaR and ΔCoVaR estimations will be shown and discussed. The conditional estimations will be time varying and hence allow us to explore the abovementioned risk measures from a time perspective. The section closes with a comparison of the two and then a summarising conclusion of the overall results.

7.1 Summary statistics

As mentioned in the data section, daily closing stock prices of 37 stocks included in the OMX Nordic 40 index are used in this essay during the period January 2002 to March 2014. To avoid problems of non-stationarity, the data was made stationary by first differencing closing prices and obtaining time series expressed in returns. A Dickey-Fuller test for unit root was performed to confirm stationarity (see Appendix 5 for statistics). The following table summarises descriptive data characteristics of sector specific returns according to the sector specification presented before. Firm specific summary statistics can be found in Appendix 3.

Table 2 Summary statistics of sector returns (2002.01-2014.03)

	Mean	St. Dev	Max	Min	Kurtosis	Skewness
Transportation	0,0005223	0,0214158	0,2632462	-0,1299304	11,4520187	0,7966252
Manufacturing	0,0007297	0,0236466	0,1919638	-0,1648135	6,0878498	0,2877235
Health care	0,0006575	0,0177065	0,1441611	-0,1732980	9,5742275	-0,1285566
Automotive	0,0006183	0,0204000	0,2263155	-0,1375964	11,5062478	0,7262372
Consumer products	0,0004443	0,0185930	0,1453922	-0,1374255	6,6813510	0,1990678
Financials	0,0004892	0,0215071	0,1711019	-0,1560362	7,6671372	0,2384631
Telecommunications	0,0000898	0,0236687	0,2426828	-0,2684559	11,1101745	-1,4760878
Utility	0,0006421	0,0179508	0,1460123	-0,1138107	6,5861114	0,1726621
Construction	0,0004392	0,0194579	0,1688312	-0,1267606	5,8886116	0,3744094
Forestry	0,0000841	0,0221167	0,1385875	-0,1037535	3,2291113	0,2312438
OMXN40	0,0002077	0,0154812	0,0982941	-0,0834942	4,1374863	0,1259259
EUROSTOXX50	0,0000582	0,0152616	0,1100183	-0,0788006	5,3449288	0,2054471

Daily average return is largest for the Manufacturing sector with 0,073% and smallest for the EuroStoxx50 index, as well as Telecommunications and Forestry sectors. Another way of expressing risk is by calculating the volatility, as measured by the standard deviation, of returns. We observe that the Manufacturing and Telecommunications industry present highest volatility with 2,36 % and 2,37 % respectively. Telecommunications and Transportation sectors show the highest observed return during the time period and Telecommunications also shows the lowest observed return.

Observing the kurtosis and skewness of the returns data, it is quite obvious that returns are not normally distributed (a normally distributed variable should optimally exhibit kurtosis of 3 and skewness of 0). A Jarque-Bera test for normality was also performed to confirm the numerical results (see Appendix 4 for statistics). VaR, CoVaR and ΔCoVaR estimation using the bivariate GARCH technique, mentioned in the estimation section, would consequently not work well as a proper estimation method. The t-distribution with a scale parameter would be a better fit in case one wants to estimate VaR, CoVaR and ΔCoVaR using GARCH models. Another approach when dealing with heavy tailed returns is to use extreme value theory.

The EuroStoxx50 volatility index, S&P500 closing prices as well as the 3 month Euribor interest rate were used as macro variables in the conditional estimations of VaR, CoVaR and ΔCoVaR, with descriptive statistics in table 3. To avoid problems with non-stationary data, the three variables were made stationary by taking first differences. Stationarity is confirmed by a Dickey-Fuller test for unit root, with results presented in Appendix 5.

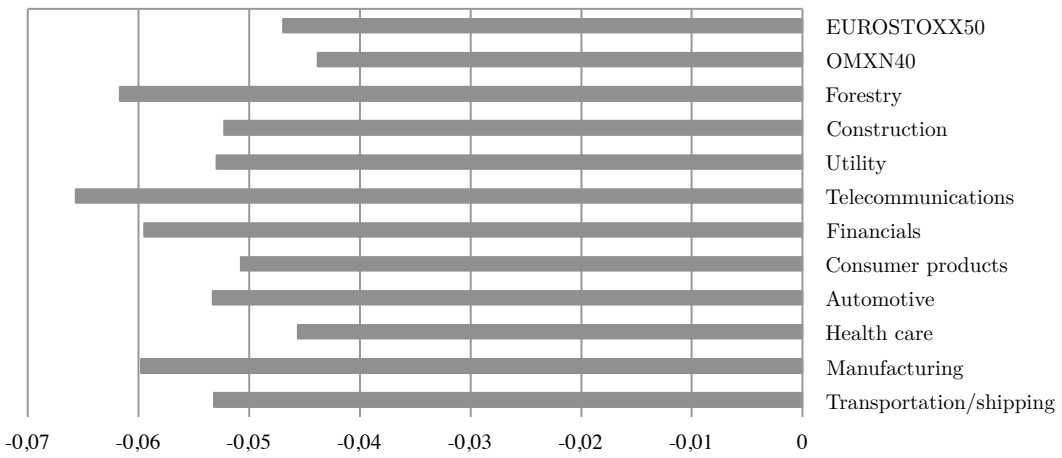
Table 3 Summary statistics of macro variables (2002.01-2014.03)

	Mean	St. Dev	Max	Min	Kurtosis	Skewness
EuroStoxx Volatility	0,0014986	0,0581252	0,3877376	-0,2205645	4,3838966	1,1572175
S&P500 return	0,0002340	0,0127164	0,1158004	-0,0903498	9,7401497	0,0077316
3 month Euribor	-0,0007131	0,0068115	0,0582878	-0,1435257	70,5160008	-2,8269315

7.2 Unconditional estimates of systemic risk contribution

To get a first overview of firms' riskiness in terms of VaR, we present the unconditional daily 1%-VaR of the Nordic stock market and the European stock market, as proxied by the OMX Nordic 40 index and the EuroStoxx50 index respectively, together with sector specific estimates. To facilitate graphical representation, firm specific tables are found in Appendix 6.

Figure 1 Unconditional sector 1%-VaR (2002.01-2014.03)



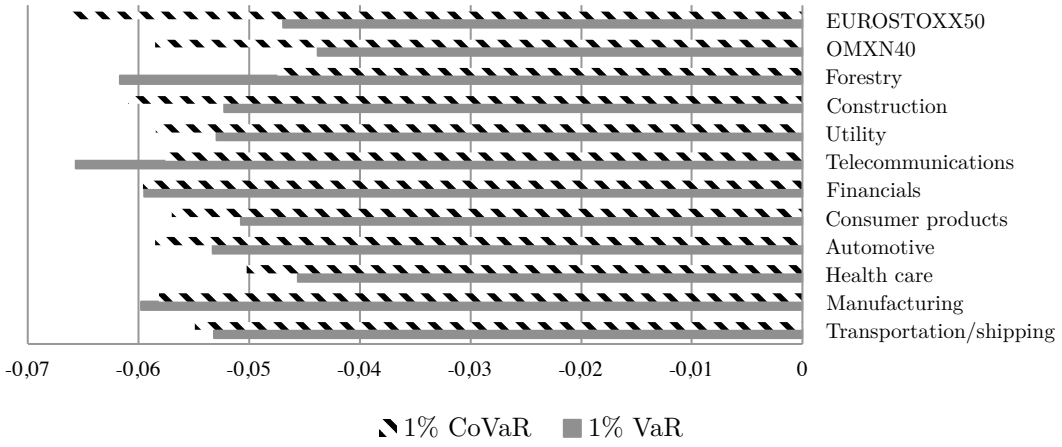
As presented in the methodology section, VaR was constructed using the estimated coefficients from the QR (see Appendix 2 for list of coefficient estimates). Since the VaR estimations are based on daily returns, all 50%-VaR estimation were zero (apart from OMXN40 50%-VaR which was 0,00033)which is why 50%-VaR estimates are not presented in the unconditional results.

Studying figure 1 above, we can conclude that Telecommunications, Forestry and Manufacturing are the three sectors that have highest (in absolute value) day 1%-VaR. Health care, Consumer products and Construction are found to have the lowest corresponding VaR. For intuition, a 1%-VaR of -0,04563 of the Health care sector means that this sector, or a portfolio consisting of firms in this sector, will not lose more than 4,563 % during a day with 99% certainty.

The sector(s) with highest VaRs are of course the most interesting to examine in terms of risk management purposes. Telecommunications was the sector with highest volatility of returns, as measured by its standard deviation. Not surprisingly, risk, as measured by volatility of returns, is positively correlated with risk as measured by VaR, as we can see from the descriptive statistics.

In figure 2 below we present 1%-VaR together with 1%-CoVaR. As explained in the methodology section, unconditional CoVaR is estimated by running a QR involving two variables; in this case, system (OMX Nordic 40) returns as dependent variable, regressed on a constant and the returns of the firm (or sector). For all 10 sectors, as well as for the European system, the above regression was performed - i.e. in figure 2, the names on the right hand side represent the independent variables in the regressions. Only for CoVaR of EUROSTOXX50, OMXN40 served as the independent variable.

Figure 2 Unconditional sector 1%-VaR and 1%-CoVaR (2002.01-2014.03)



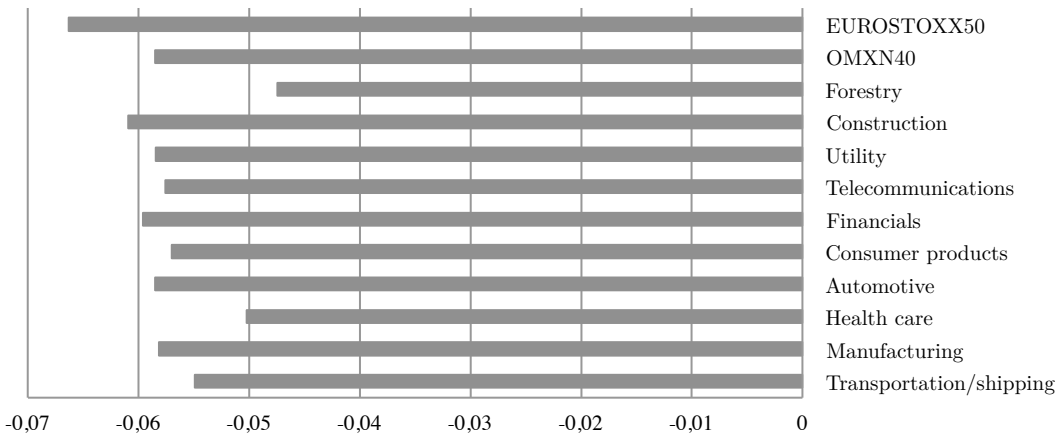
For intuition, CoVaR is the VaR of the Nordic system conditional on a sector being in distress (i.e. on its 1%-VaR level). Hence, it is the maximum loss incurred by the Nordic market (as proxied by the index) when a sector is found to be on it's 1%-VaR level, on a daily basis and with 99% certainty. For example, when the sector Health care is on its 1%-VaR level, then the 1%-VaR of the Nordic stock market is -0,05024.

What is interesting in this figure is that we can compare the Nordic stock market's VaR conditional on a sector's and European stock market's 1%-VaR. This is a way of identifying spillover effects on the Nordic stock market arising from different sectors on this market. Observing only 1%-CoVaR in isolation, we can identify what sectors have highest spillover effects on the Nordic stock market. Since this is not the aim of the essay, but a step necessary calculating ΔCoVaR, we only consider these results briefly.

Looking at the 1%-CoVaR spikes in isolation, the largest spillover effects to the Nordic stock market seem to arise from the European stock market and Construction and Financials sectors. However, Utility, Consumer products, Health care and Automotive sectors also have spillover effects onto the Nordic market that are larger than their risk seen in isolation. What is further interesting is that those sectors having largest individual VaRs are at the same time characterised by having lowest CoVaRs. So, even though a sector experiences a large VaR, which is a bad thing, this risk does not seem to spill over to the same extent, which is a good thing. To summarise, as opposed to a sector's risk in isolation, as measured by 1%-VaR, the 1%-CoVaR risk measure is larger than 1%-VaR in 6 out of 10 sectors. This indicates that interconnectedness and linkages do have a role.

Figure 3 below illustrates each sector's marginal risk contribution to overall systemic risk of the Nordic stock market. As before, the names on the right-hand side indicate the independent variable of a quantile regression where Nordic system returns is the dependent variable (or the European system in the case of OMXN40). To recapitulate, marginal systemic risk contribution, as measured by ΔCoVaR, was calculated as the difference between 1%-CoVaR and 50%-CoVaR.

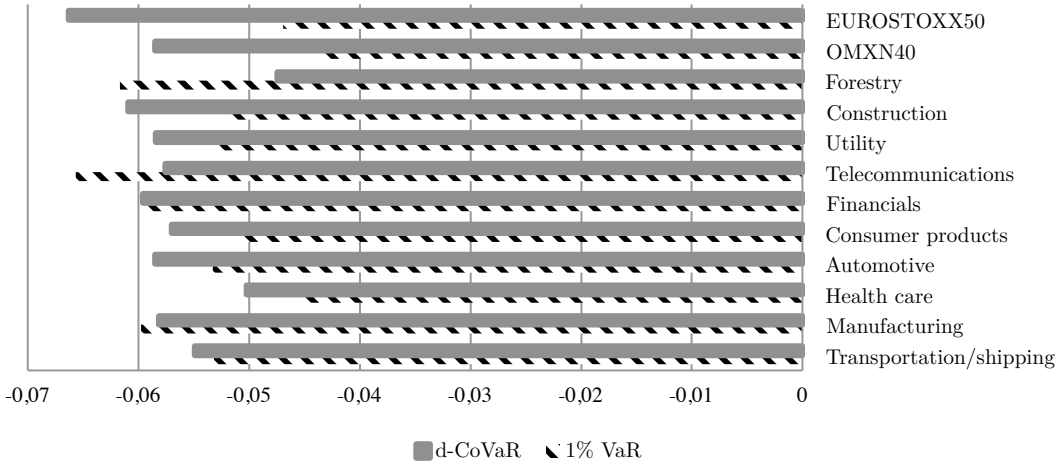
Figure 3 Unconditional sector ΔCoVaR (2002.01-2014.03)



Unconditional ΔCoVaR appears to be the largest for the EuroStoxx50 variable. In practice, this means, not unexpectedly, that the European stock market contributes the most to over all systemic risk on the Nordic stock market. Taking a closer look at which particular sectors in the Nordic stock market that contribute most to Nordic stock market systemic risk, we find Construction, Financials and Automotive sectors. The sectors contributing the least are Forestry, Health care and Transportation. For intuition, ΔCoVaR measures how much an institution's transition, from being at median state (at 50%-VaR) and then going into financial distress (1%-VaR), contributes to the VaR of the Nordic stock market.

Figure 4 below illustrates unconditional 1%-VaR and ΔCoVaR, i.e. we can observe the riskiness of a firm in isolation versus its marginal contribution to overall systemic risk.

Figure 4 Unconditional sector 1%-VaR and ΔCoVaR (2002.01-2014.03)



As previous research show, we observe that ΔCoVaR is larger (in absolute value) than 1%-VaR in the majority of cases, and sectors having a large VaR generally seem to have a large ΔCoVaR. In three cases; Forestry, Telecommunications and Manufacturing, we can observe a 1%-VaR that is larger than their corresponding ΔCoVaR.

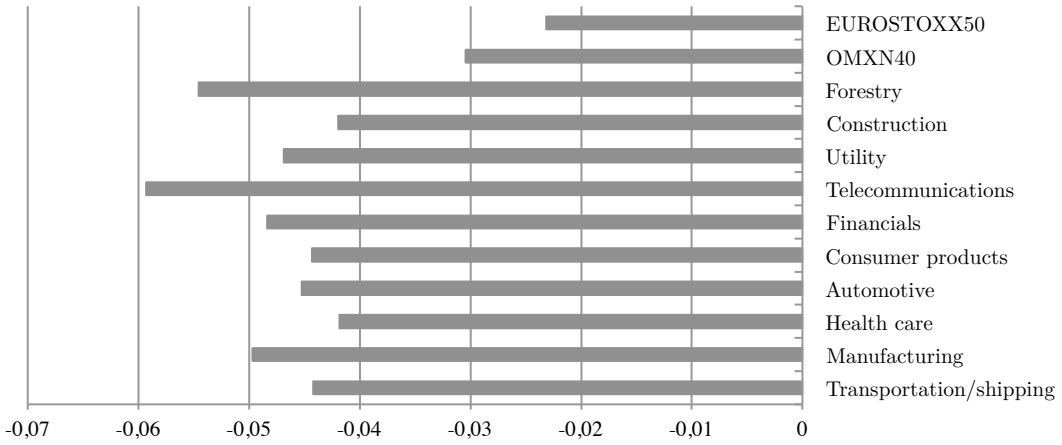
Referring to previous research, one of the main conclusions drawn was that VaR is probably not sufficient when it comes to measuring and managing risk. This is also confirmed here – in the majority of cases, spillover effects as measured by CoVaR, are larger than risk as measured by VaR. Another conclusion in disfavour of VaR is the fact that ΔCoVaR, in 3 out of 10 sectors, was measured as being larger than 1% VaR. This is a serious problem; when a firm's risk in isolation is smaller than the contribution that firm has to overall systemic risk. It confirms the importance of monitoring interconnectedness and financial linkages between firms and sectors, rather than looking at, and basing regulating on, firm risk in isolation.

7.3 Conditional estimates of systemic risk contribution

As mentioned in the methodology section, conditional estimation of VaR, CoVaR and ΔCoVaR allows us to examine how mentioned risk measures evolve over time. We include additional variables in the estimations that are assumed to explain stock returns and that can be assumed to capture the time varying nature of risk. The inclusion of macro variables also allows us to produce estimates that are more refined relative to the unconditional constant measures that only give us a single output.

We begin by examining the conditional average 1% -VaR for the 10 sectors and two market indices, as illustrated in figure 5 below.

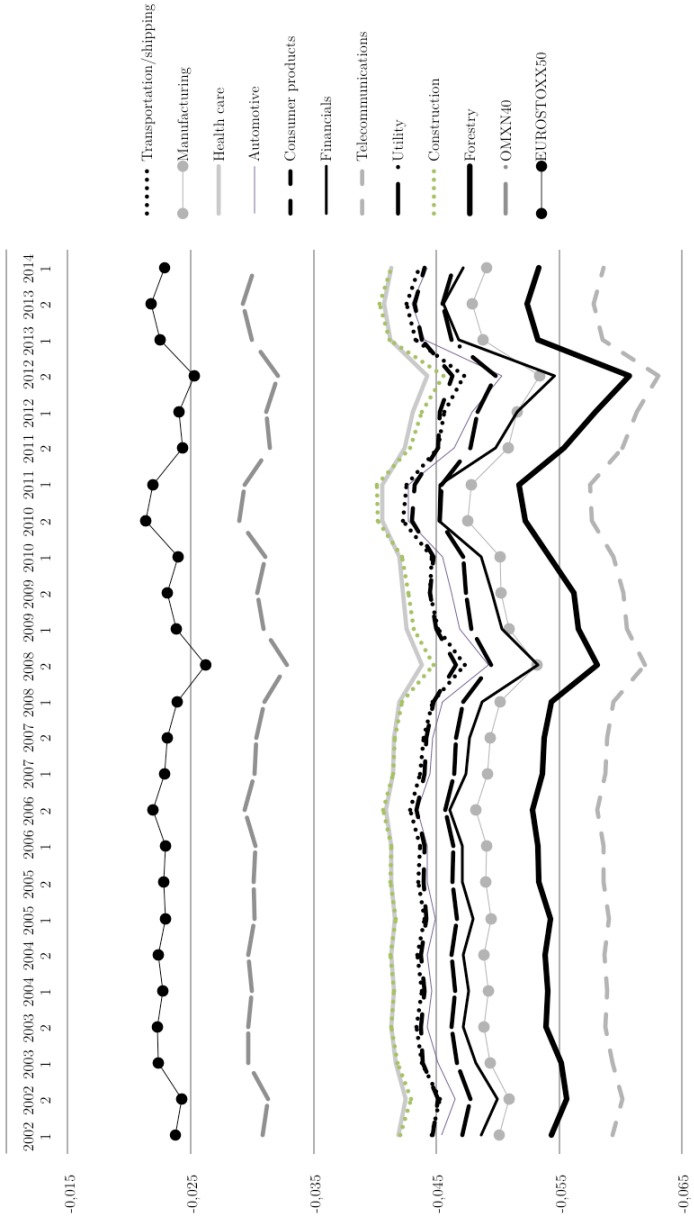
Figure 5 Conditional average sector 1%-VaR (2002.01-2014.03)



In accordance with our unconditional measures of VaR; Forestry, Manufacturing and Telecommunications are the three sectors having the, on average, highest (in absolute value) individual risk as measure by 1% VaR.

To capture the evolution of 1%-VaR series during the period 2002-2014 we plot thirteen averages that represent VaR on a semi annual basis, i.e. two times per year (July and December) each year during 2002-2013 and until 31st of March 2014. In the figure we can track the evolution of VaR during different time periods, including for example the financial crisis.

Figure 6 Conditional semi annual average sector 1%-VaR (2002.01-2014.03)



As figure 6 shows, the pattern over time is similar over different sectors and we get a clear distinction of what sectors had highest VaRs and when. As expected, we have drops in VaR in 2008-2 and 2012-2. The first drop refers to the global financial crisis, and the second drop most likely refers to the (ongoing) Eurozone crisis. We observe the EuroStoxx50 Index having the smallest average VaR (in absolute value) during the time period and we find Telecommunications and Forestry sectors having largest VaRs.

Continuing to the conditional CoVaR estimations, 1% and 50%-CoVaR figures are presented below. As mentioned before, figures 9 and 10 present the semi annual

evolution of VaR of the Nordic stock market (as proxied by the OMX Nordic 40 index) conditional on each sector being at its 1% and 50%-VaR level. Figures 7 and 8 present total averages in order to get a snapshot estimate of the conditional CoVaR.

Figure 7 Conditional average sector 1%-CoVaR (2002.01-2014.03)

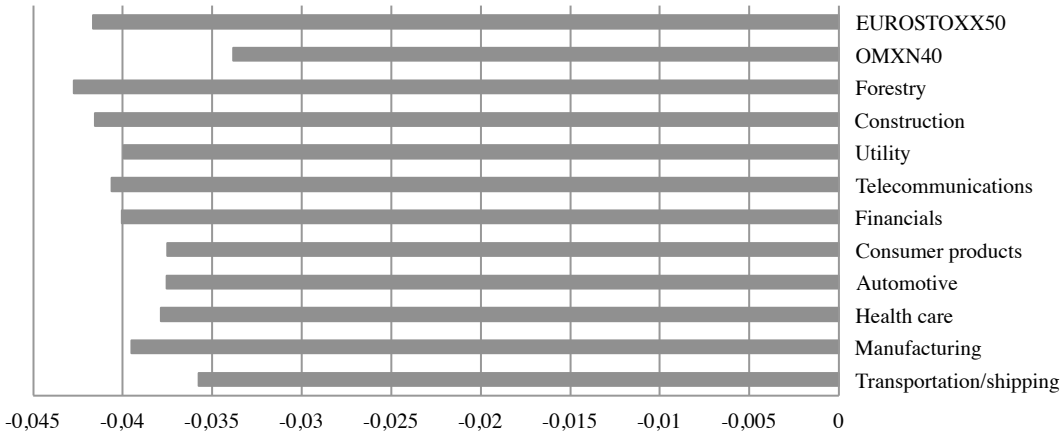
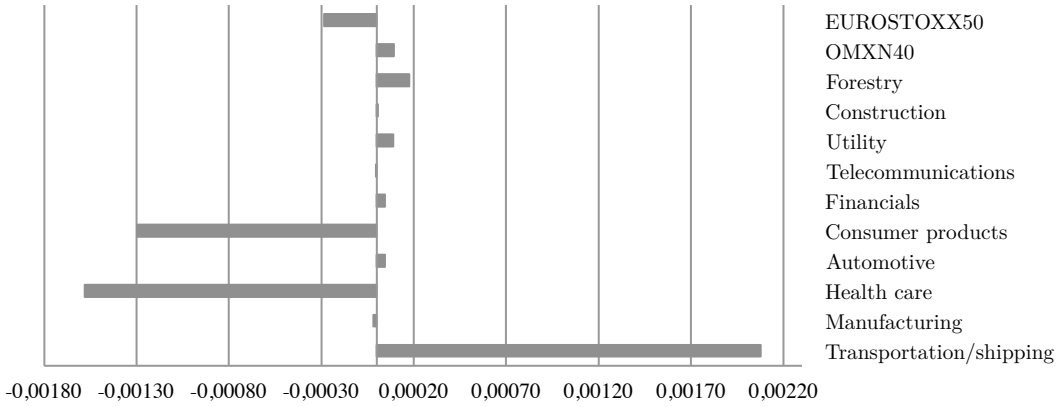


Figure 8 Conditional average sector 50 %-CoVaR (2002.01-2014.03)



The three sectors impacting the 1%-VaR of the Nordic stock market are Forestry, Construction and the EuroStoxx50 index. Apart from Forestry, the other two sectors were not among those having largest 1%-VaR. Observing the 50%-CoVaR averages, Consumer products and Health care are the two sectors having an impact on the Nordic system 1% VaR during median state. Below we plot semi annual estimates of CoVaR in order to get a time-varying illustration. Recapitulating the intuition of CoVaR; a 1% CoVaR of for example Utility, at -0,04, means that the Utility sector, being at it's 1%-VaR level, affects the VaR of the Nordic system by -0,04, i.e. -4%. In the same fashion, 50% CoVaR of the Consumer products sector of -0,00130 means that this sector, being in its median state, affects the VaR of the Nordic system by -0,130%.

Figure 9 Conditional semi annual average sector 1%-CoVaR; system VaR conditional on sector i being at its 1%-VaR, and macro variables (2002.01-2014.03)

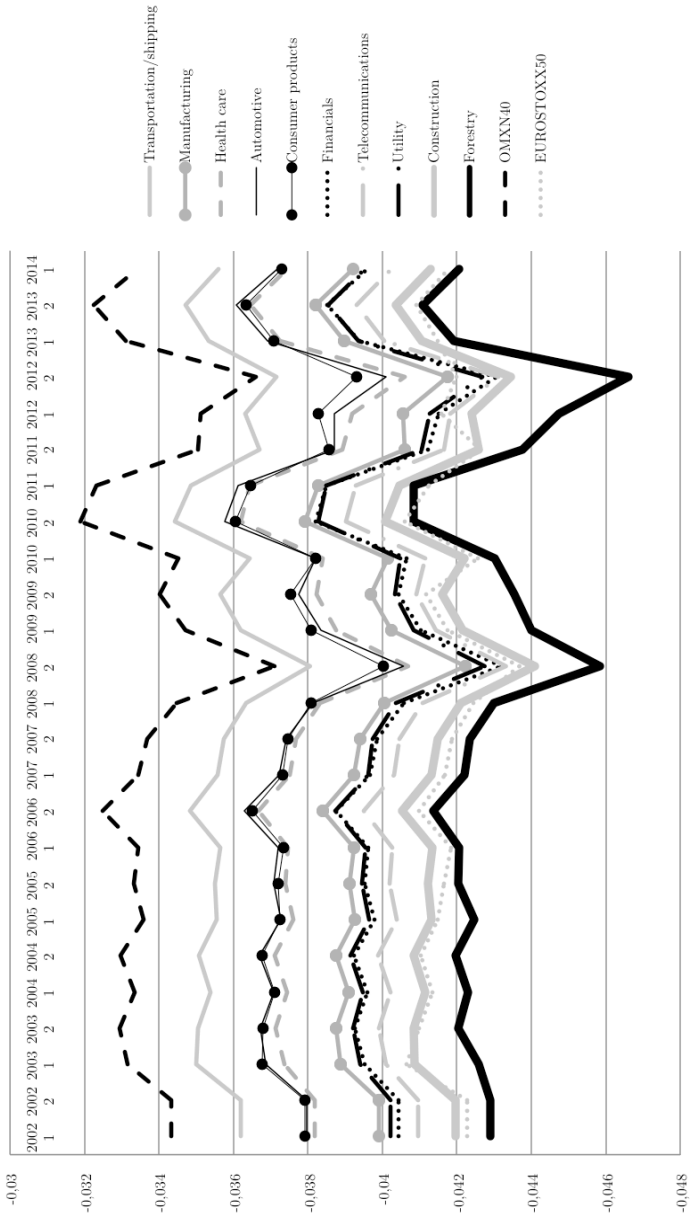
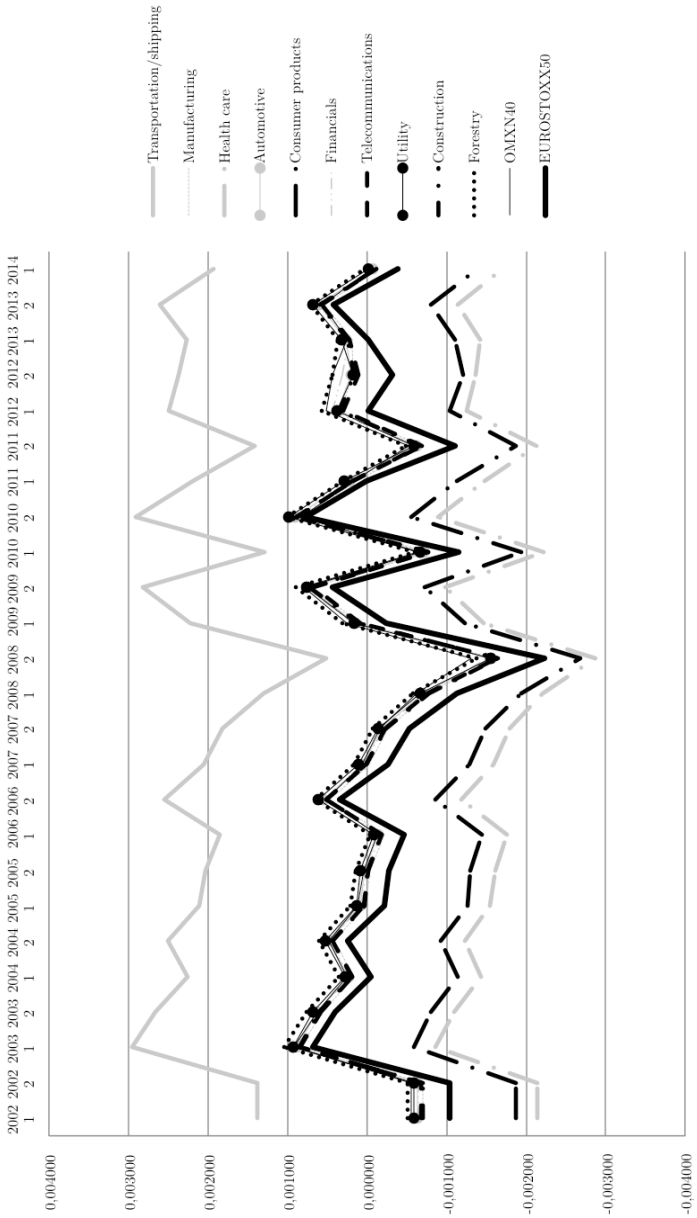


Figure 10 Conditional semi annual average sector 50%-CoVaR; system VaR conditional on sector i being at its 1%-VaR, and macro variables (2002.01-2014.03)

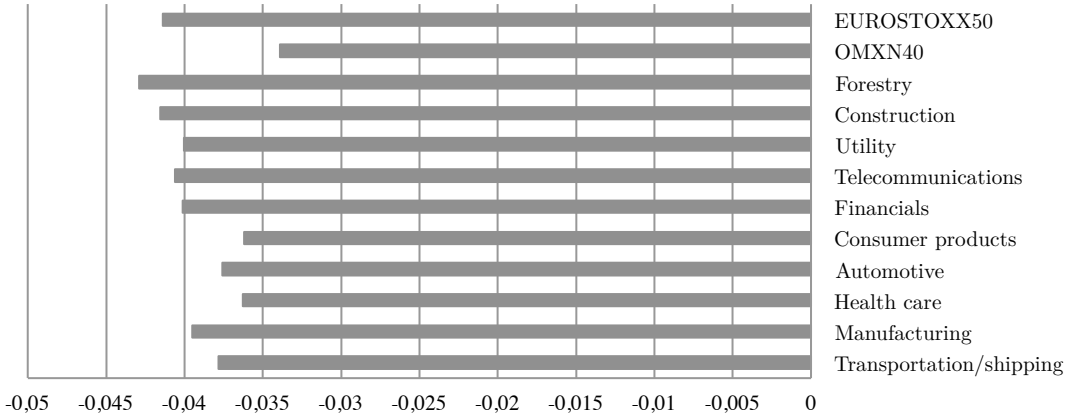


Again, we observe two drops; one in 2008 and one in 2012, related to the previously mentioned financial events. From these illustrations we can also conclude that sectors usually affect the Nordic system in a similar way; the graphs rarely cross and all sectors follows a similar pattern over time. What also can be observed is that there is more uncertainty in how firms affect the overall market when they are at their 50% VaR level, than when they are in financial distress.

Having presented the conditional VaR and CoVaR estimates, ΔCoVaR will now be illustrated in the same fashion. For an intuitive overview of what sectors contribute

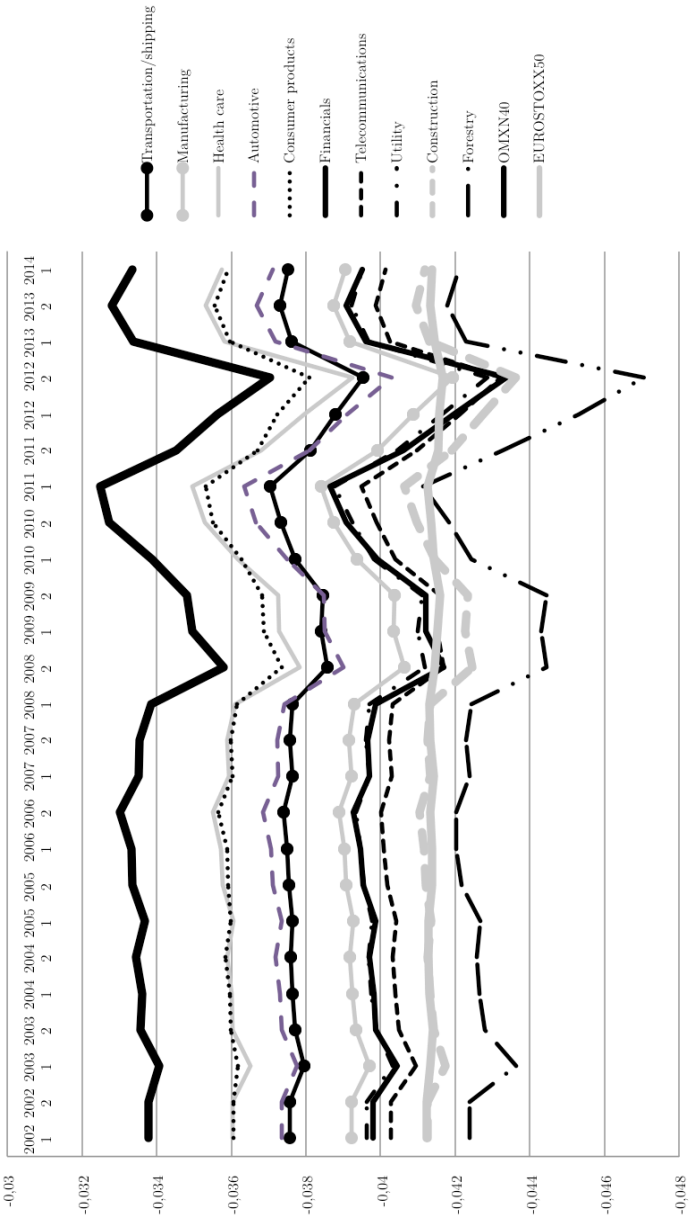
the most to the Nordic stock market, conditional average sector ΔCoVaR estimates are presented in figure 11 below.

Figure 11 Conditional average sector ΔCoVaR (2002.01-2014.03)



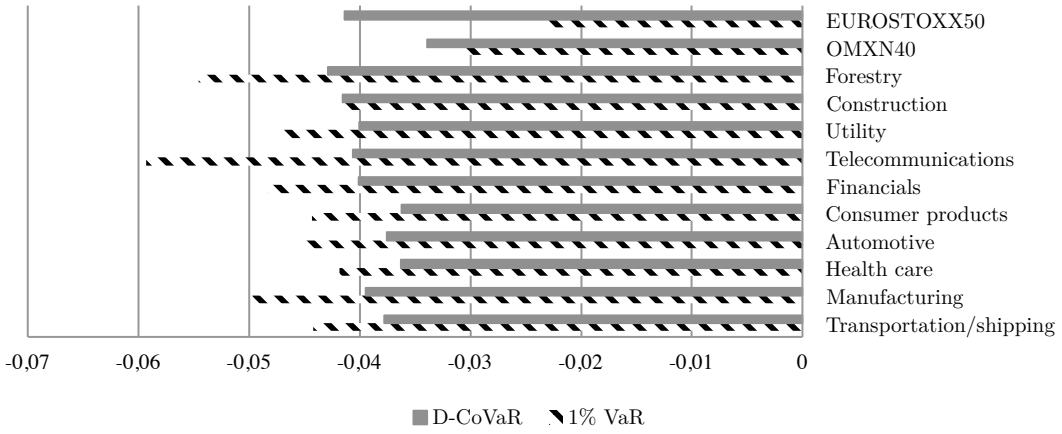
For intuitive purposes, the meaning of ΔCoVaR is that it shows how much the VaR of the Nordic system is affected when a sector goes from being in median state into financial distress, i.e. going from being at its 50%-VaR level to its 1%-VaR-level. The sectors contributing the most to Nordic stock market systemic risk on average, as measured by ΔCoVaR, are Forestry, Construction and the EuroStoxx50 index (or more intuitively the European stock market). We find the Consumer products, Automotive and Health care among the sectors contributing least. Taking semi-annual averages during the examined period, we obtain a (shorter) time-varying series of ΔCoVaR of the different sectors and indices. Again here, we observe a drop in 2008 and 2012, however the latter is more pronounced from a ΔCoVaR perspective, where systemic risk contribution was largest during this time of financial distress.

Figure 12 Conditional semi annual average sector ΔCoVaR; how much a sector i contributed to system VaR by going from its 50%-VaR to its 1%-VaR (2002.01-2014.03)



Unlike VaR, CoVaR and ΔCoVaR measure risk conditional on another entity i being in financial distress. It is therefore important to compare 1%VaR estimates with ΔCoVaR estimates in order to examine not only the entity in isolation but the entity in connection to other entities, as we have seen these two can differ. As we have observed in the conditional VaR, CoVaR and ΔCoVaR estimations, as well as in previous research, VaR was not regarded presenting a sufficient estimate of risk due to the interconnectedness of entities. In figure 9 below, we observe averages of sector 1% VaR and sector ΔCoVaR.

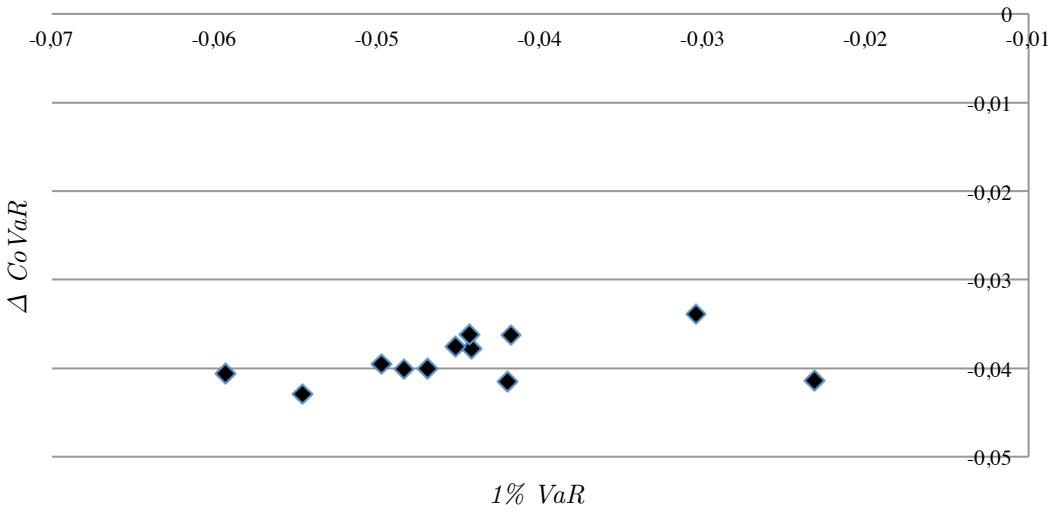
Figure 13 Conditional average sector 1%-VaR and ΔCoVaR (2002.01-2014.03)



We observe that 1%-VaR is larger in all 10 sectors, i.e. the risk of a sector in isolation is larger than the risk that it contributes with to the Nordic stock market. For intuition, the ΔCoVaR measures the change, in per cent, of the Nordic stock market's 1%-VaR when a sector i is moving from its 50%-VaR to its 1%-VaR. For example, the ΔCoVaR reported by the Forestry industry is -0,0429; this means that the 1%-VaR of the OMX Nordic 40 is affected by 4,29 % when the VaR of the Forestry sector moves from being at its 50%-VaR level into financial distress, i.e. 1%-VaR.

Further, confirming previous research, a (visible) positive relationship between 1%-VaR and ΔCoVaR is not found in this essay as the plot of figure 10 below suggests.

Figure 14 Plot of conditional average sector 1%-VaR on horizontal axis and ΔCoVaR on vertical axis (2002.01-2014.03)



The results of the conditional estimations also support findings from previous research. The first concerns the finding that there seems not to be any (positive) relationship between 1%-VaR and ΔCoVaR; i.e. a high entity VaR does not necessarily translate into a high ΔCoVaR. The results also imply that ΔCoVaR is higher during distress periods than during times of financial prosperity. The sectors contributing the most to Nordic systemic risk are Forestry, Construction and Telecommunications sectors. No sectors show a higher ΔCoVaR than their corresponding stand-alone 1%-VaR, which is positive. Although, considering EuroStoxx50 impact on Nordic systemic risk, we find a ΔCoVaR that is almost twice as large as its stand-alone risk measured by 1%-VaR.

In comparison to the unconditional ΔCoVaR estimates, where in some cases 1%-VaR was larger than ΔCoVaR, all ΔCoVaR estimates in the conditional estimations were below their respective 1% VaR estimates. Since the conditional estimation differs from the unconditional only by the additional included macro variables, it is reasonable to conclude that the difference is due to the inclusion if these variables. As previously mentioned, the inclusion of additional explanatory variables in the VaR and CoVaR estimations yields estimates that control for these variables, i.e. we can distinguish the effect the variables might have on the estimates of VaR, CoVaR and ΔCoVaR.

The analysis performed in this essay is a system-to-entity analysis. One could easily obtain entity-to-entity estimates (i.e how a given sector's (or even firm's) 1%-VaR changes when another sector (or firm) realises it's 1%-VaR level) by implementing the same techniques; this will be illustrated in a case study by using banks on the OMX Nordic 40 index, in the section that follows. Another possibility is to examine how an entity, or system, reacts when several sectors reach their 1% VaR levels, at the same time.

8 Case study: Risk linkages of Nordic banks

In addition to analysing firms on the Nordic market, it is important to analyse banks in particular, on this market. Nordic firms most likely rely on credit from Nordic banks, and Nordic banks most likely have these Nordic firms as their customers. Given this connection of banks to, essentially, the whole Nordic economy makes them important in terms of their systemic position towards other banks. Contagion and spillover effects are considered most prevalent in the financial system because of these interconnections. It is therefore of specific importance to measure how risk of one bank affects the risk of another bank, in addition to examining how much these banks contribute to overall systemic risk, which we considered in the previous section.

This short case study serves as a complement to this essay and demonstrates an entity-to-entity analysis with help of ΔCoVaR. Interpretation is not different than before, only in this case we are able to narrow down the analysis and examine a sector that is important to all other sectors examined in this essay. The same methodology and estimation technique is used as before, however only conditional estimations of VaR, CoVaR and ΔCoVaR are performed due to the refined nature of conditional estimation. VaR is calculated as before (equations 14 and 15), and instead of treating the system (OMX Nordic 40, EuroStoxx50) as the dependent variable (as in equations 18 and 19), we now regress each bank i on each bank j in the sample, i.e we get an entity-to-entity analysis, instead of an entity(sector)-to-system analysis. As before, the quantile of interest is 1%.

$$X_t^{bank\ i|bank\ j}(q) = \alpha_q^{i|j} + \beta_{q,1}^{i|j} X_t^i + \sum \beta_{q,2}^{i|j} M_t + \varepsilon_t^{i|j} \tag{22}$$

$$CoVaR_t^{bank\ i|bank\ j}(q) = \widehat{\alpha}_0^{i|j} + \widehat{\beta}_{q,1}^{i|j} VaR_t^j(q) + \widehat{\beta}_{q,2}^{i|j} M_t \tag{23}$$

$$\Delta CoVaR_t^{bank\ i|bank\ j}(q) = CoVaR_t^{bank\ i|bank\ j}(q) - CoVaR_t^{bank\ i|bank\ j}\left(q = 50\%\right) \tag{24}$$ [4]

In the table below we find the individual 1% conditional (average) VaR of the chosen banks; *Danske Bank, Nordea, SEB* and *Swedbank.* [5]

Table 5 1% and 50 % conditional average VaR of Danske bank, Nordea, SEB and Swedbank (2002.01-2014.03)

	DANSKE BANK	**NORDEA**	**SEB**	**SWEDBANK**
1%-VaR	-0,053257	-0,049321	-0,054985	-0,057739
50%-VaR	-0,000097	-0,000139	-0,000104	0,000246

Looking at bank risk in isolation, as measured by their 1%-VaR, we observe in table 1 that Swedbank is considered the most risky and Nordea the least risky. Next we estimate the 1% conditional average CoVaR of bank i given that another bank j is in financial distress (at its 1%-VaR level), with results presented in table 6 below. The regression in equation 22 is run three times for each bank, and then CoVaR is constructed using the estimated coefficients as in equation 23. On the top horizontal row in table 6 we find the dependent variables and the vertical left column represents the conditioning, independent, variables in addition to the macro

[4] Coefficient estimates in appendix 7

[5] The attentive reader might notice that one of the major Nordic banks, Handelsbanken, is missing. This does however not affect the results.

variables. The 1% CoVaR estimation captures the spillover effects arising from a bank *j* falling into financial distress.

Table 6 1% conditional CoVaR with conditioning variable on vertical axis (bank i) and dependent variable on horizontal axis (bank j), i.e. 1% VaR of bank *j* conditional on bank *i* being at its 1% -VaR

	DANSKE BANK	**NORDEA**	**SEB**	**SWEDBANK**	***Average***
Danske	-	-0,06256	-0,07656	-0,07644	*-0,07185*
Nordea	-0,06253	-	-0,07696	-0,07496	*-0,07148*
SEB	-0,05683	-0,06675	-	-0,07931	*-0,06763*
Swedbank	-0,06382	-0,06634	-0,08076	-	*-0,07030*
Average	*-0,06106*	*-0,06522*	*-0,07809*	*-0,07690*	-

Observing the results in the table above, spillover is considered as largest from Danske Bank, with an average spillover effect of 7,185 % and Nordea with 7,148 %. This seems rather logical as regards to their size; Nordea and Danske Bank are considered as the largest banks in the Nordic region as measured by their asset size. For example, 1%-CoVaR of Danske bank of -0,06253 means that when Nordea reaches its 1%-VaR level, the VaR of Danske Bank is affected by 6,253%. The VaRs of SEB and Swedbank are considered to be affected the most when other banks are in financial distress.

In order to quantify how much each bank contributes to the risk of another bank we now consider ΔCoVaR, as defined in equation 24 and with results in table 7.

Table 7 ΔCoVaR of banks; i.e. how much bank *j*'s (horizontal axis) VaR is affected when bank *i* (vertical axis) goes from being in median state (50%-VaR) into financial distress (1%-VaR)

	DANSKE BANK	**NORDEA**	**SEB**	**SWEDBANK**	**Average**
Danske	-	-0,06241	-0,07643	-0,07644	*-0,07176*
Nordea	-0,06244	-	-0,07683	-0,07496	*-0,07141*
SEB	-0,05692	-0,06669	-	-0,07931	*-0,06764*
Swedbank	-0,06383	-0,06639	-0,08086	-	*-0,07036*
Average	*-0,06106*	*-0,06516*	*-0,07804*	*-0,07690*	-

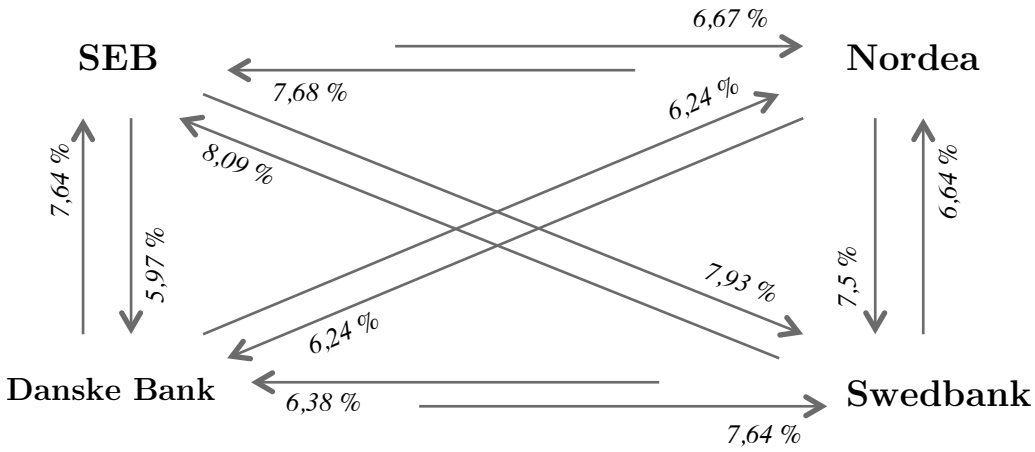
To recapitulate, the interpretation of ΔCoVaR is as follows; for example, Danske Bank's ΔCoVaR of -0,06244 means that the 1%-VaR of Danske Bank is affected 6,244% when Nordea goes from being in median state (50%-VaR) into financial distress, i.e. being at its 1%-VaR. By looking at the average values and making this interpretation, we can see that Nordea is the bank that is assumed to be least unaffected by the other banks in the sample moving from a median state into financial distress. In the same fashion, SEB is considered most vulnerable, or unstable. Danske bank is considered to be the bank affecting the other banks the most, and Swedbank is considered the bank with smallest influence. This seems logical as Swedbank is the smallest of the banks considered, and Danske bank is

considered as one of the largest (after Nordea). These conclusions also confirm previous research on size being a predictor of ΔCoVaR.

Connecting to risk in isolation as opposed to contribution to other banks' risk, we saw in table 5 that Swedbank was considered the most risky and Nordea the least. In table 7 (in the vertical average column) we however observe that Nordea is one of the banks affecting the VaRs of other banks the most. This again confirms the previously observed conclusion that just because an institution is risky in isolation, does not mean that it spills this risk over and has an impact on other institutions to the same extent.

For a more appealing risk contribution illustration, we present the picture below illustrating each bank's ΔCoVaR; i.e. how much the VaR of bank i is affected if bank j moves from it's median state (50%-VaR) into financial distress (1%-VaR), all other things equal.

Figure 15 Illustration of how each bank is affected by another bank moving from it's 50%-VaR to its 1%-VaR, i.e. the ΔCoVaR's of Danske bank, Nordea, SEB and Swedbank



9 Summary and conclusions

The aim of this essay was to measure systemic risk contribution of Nordic firms and answer the question what firms contribute most to systemic risk of the Nordic stock market. Measuring spillover effects and systemic risk contribution of sectors, as measured by their CoVaR and ΔCoVaR respectively, is an important means of assessing risk both for the firm in isolation, but also for regulators and the economy as a whole, when financial markets are growing and becoming more integrated.

The CoVaR methodology proposed by Adrian and Brunnermeier (2011) involves estimating a "conditional" VaR, i.e. the (1%) VaR of a financial system, given an

institution i being in financial distress. Simply put, it is a measure of how the institution being in financial distress affects the VaR of the overall financial system it is included in. In order to obtain how much the institution contributes to systemic risk of the system, a median state CoVaR is calculated for the system, i.e. how much (1%) VaR of the system, is affected by the institution being in median state, i.e. on 50%-VaR. ΔCoVaR is obtained by taking the difference between the two. The methodology can be implemented using different estimation methods, but the most common and straightforward method, and the one used in this essay, is quantile regression.

This "conditional" VaR can be estimated in a conditional and unconditional way. A conditional estimation of CoVaR involves conditioning on a set of macro variables that are assumed to explain stock returns; in this way we obtain a time-varying measure. The unconditional estimation yields estimates based on historical simulation and produces a constant measure of CoVaR and ΔCoVaR based on previous returns data only. Estimations were performed on a sample of 37 stocks' returns listed on the OMX Nordic 40 Index, consisting of Swedish, Danish and Finnish stocks, denominated in SEK, DKK and EUR, covering the period January 2002 to March 2014. Due to limited space, firm specific results were aggregated into sector specific results, representing the following ten sectors: *Transportation, Manufacturing, Health care, Automotive, Consumer products, Financials, Telecommunications, Utility, Construction* and *Forestry.*

The results indicate that there is no (visible) positive relationship between an institution's VaR and its ΔCoVaR, as one might think, i.e. just because an institution is risky in isolation, as measured by its VaR, it is not necessarily the case that is contributes most to systemic risk. However, in three cases (Forestry, Telecommunications and Manufacturing) we observe a 1% VaR that is larger than the sectors' corresponding ΔCoVaRs, indicating that their contribution to systemic risk is larger than their risk in isolation, as measured by unconditional VaR and CoVaR. On the other hand, sectors with a high volatility of returns tended to have a high VaR also.

The results also indicate that different sectors affect the VaR of the financial system differently. Among those having highest spillover effects measured by CoVaR were the Construction and Financials sectors as well as the European stock market. Turning to what sectors contribute the most to Nordic systemic risk, we logically find the European stock market, as well as the Construction, Financials and Automotive sectors. Forestry, Health care and Transportation are the sectors concluded to contribute least to Nordic systemic risk.

Turning to the conditional estimations, i.e. VaR, CoVaR and ΔCoVaR estimations conditioned on macro variables representing the business cycle, trend and

expectations and investor sentiment, they yield similar results to the unconditional estimates. What separates them is that we now control for market-specific "risks" and events that apply to all firms, in order to obtain a refined estimate. The principal difference was that all ΔCoVaR estimates were above (in absolute value) their respective VaR estimates, indicating that all institutions contributed less to systemic risk than they were risky in isolation. Here we find the European stock market and Forestry and Construction sectors contributing the most to Nordic systemic risk, which is different than from the unconditional estimations were Forestry was one of the sectors contributing the least. We also observe that contribution to systemic risk and spillover effects, as measured by ΔCoVaR and CoVaR respectively, are higher in periods of financial distress than in other periods, i.e. negative financial events seem to have greater impact than positive.

As a special case study, the relationship between the banks included in the OMX Nordic 40 index is also examined. Here, we find that Swedbank is the most risky (has the largest VaR) and Nordea the least risky, but the other way around when looking at ΔCoVaR; i.e. Nordea appears to be the bank that affects other banks the most, in this framework.

The results of this essay contribute to the growing field of research on systemic risk and risk contribution by the examination of Nordic countries. This has, until now, not yet been evaluated with the CoVaR methodology.

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Appendices 1-7

Appendix 1 List of firms included in the data, from OMX Nordic 40 Index members. Alfa Laval, Sv. Handelsbanken and ABB not included in the analysis due to problems with data.

	Stock	Currency	Sector
1	AUTOLIV	SEK	AUTOMOTIVE
2	ASSA ABLOY B	SEK	MANUFACTURING
3	ATLAS COPCO A & B	SEK	MANUFACTURING
4	ASTRAZENECA	SEK	HEALTH CARE
5	CARLSBERG B	DKK	CONSUMER PRODUCTS
6	COLOPLAST B	DKK	HEALTH CARE
7	DANSKE BANK	DKK	FINANCIALS
8	ELEKTA B	SEK	HEALTH CARE
9	ELECTROLUX B	SEK	CONSUMER PRODUCTS
10	ERICSSON B	SEK	TELECOMMUNICATIONS
11	FORTUM	EUR	UTILITY
12	GETINGE	SEK	HEALTH CARE
13	H&M B	SEK	CONSUMER PRODUCTS
14	INVESTOR B	SEK	FINANCIALS
15	KINNEVIK B	SEK	FINANCIALS
16	KONE	EUR	MANUFACTURING
17	AP MÖLLER MAERSK B	DKK	TRANSPORTATION
18	NORDEA BANK	SEK	FINANCIALS
19	NOKIA	EUR	TELECOMMUNICATIONS
20	NOKIAN RENKAAT	DKK	MANUFACTURING
21	SAMPO A	EUR	FINANCIALS
22	SANDVIK	SEK	MANUFACTURING
23	SCA B	SEK	CONSUMER PRODUCTS
24	SCANIA B	SEK	AUTOMOTIVE
25	SEB A	SEK	FINANCIALS
26	SKANSKA B	SEK	CONSTRUCTION
27	SKF B	SEK	MANUFACTURING
28	STORA ENSO R	EUR	FORESTRY
29	SWEDBANK A	SEK	FINANCIALS
30	SWEDISH MATCH	SEK	CONSUMER PRODUCTS
31	TDC	DKK	TELECOMMUNICATIONS
32	TELIASONERA	SEK	TELECOMMUNICATIONS
33	UPM KYMMENE	EUR	FORESTRY
34	VOLVO	SEK	MANUFACTURING
35	VESTAS WIND SYSTEMS	DKK	MANUFACTURING
36	NOVO NORDISK B	DKK	HEALTH CARE

Appendix 2 Quantile regression coefficient estimates for creating unconditional and conditional 1%-VaR, 50%-VaR, 1%-CoVaR and 50%-CoVaR, all necessary to construct ΔCoVaR, i.e. estimates of unknown parameters in equations 1, 3, 5, 8, 10, 14, 16 and 18.

VaR 1%	Unconditional	Conditional			
	α	α	β1 (volatility)	β2 (S&P500)	β3 (euribor)
A.P Möller Maersk	-0,05319***	-0,04386***	-0,14482***	0,38648***	0,37874***
Assa Abloy B	-0,05431***	-0,04615***	-0,14462***	0,34695***	0,71655***
Astra Zeneca	-0,04367***	-0,04168***	-0,12614***	0,16169	0,59315***
Atlas Copco A	-0,05462***	-0,04342***	-0,17688***	0,40151***	0,45949***
Atlas Copco B	-0,05882***	-0,04499***	-0,20605***	0,37798***	0,42973***
Autoliv SDB	-0,04762***	-0,04312***	-0,17391	0,23716***	0,59619***
Carlsberg B	-0,05544***	-0,05226***	-0,16392***	0,35635***	0,59411***
Coloplast B	-0,03835***	-0,03532***	-0,03635**	0,26757***	0,48324***
Danske Bank	-0,06122***	-0,05248***	-0,21142***	0,28208***	0,74472***
Electrolux B	-0,06620***	-0,05141***	-0,18350***	0,23743***	0,55498***
Elekta B	-0,05565***	-0,04926***	-0,13859***	0,03036	0,08807
Ericsson B	-0,08031***	-0,07143***	0,13358***	0,66774***	0,54199
Fortum	-0,05296***	-0,04653***	-0,14375***	0,17798***	0,35747**
Getinge	-0,04415***	-0,03934***	-0,09815***	0,01172***	-0,24532**
H&M B	-0,04552***	-0,03829***	-0,17497***	-0,00601	0,28659*
Investor B	-0,04720***	-0,03449***	-0,16382***	0,33824***	0,53783***
Kinnevik B	-0,06050***	-0,04926***	-0,26498***	0,17429*	0,65180***
Kone B	-0,04768***	-0,04195***	-0,15429***	0,18000***	0,32054
Nokia	-0,07895***	-0,07172***	-0,17206	0,13216	0,79704***
Nokian Renkaat	-0,06199***	-0,0539***2	-0,11360***	0,24112	0,14682
Nordea Bank	-0,05854***	-0,04856***	-0,19123***	0,48565***	0,83979***
Novo nordisk B	-0,04633***	-0,04211***	-0,09568***	0,13246	0,56047***
Sampo A	-0,04806***	-0,03850***	-0,13050***	0,43933***	0,57635***
Sandvik	-0,05532***	-0,04466***	-0,16279***	0,25934***	0,61524***
SCA B	-0,04082***	-0,03563***	-0,12390***	0,24484***	0,05940
Scania B	-0,05903***	-0,04629***	-0,19149***	0,35509***	0,62804***
SEB A	-0,06882***	-0,05409***	-0,28371***	0,56816***	0,84896***
Skanska B	-0,05227***	-0,04158***	-0,14434***	0,17272***	0,43471***
SKF B	-0,05150***	-0,04299***	-0,19110**	0,30602***	0,07663
Stora Enso R	-0,06167***	-0,05219***	-0,12003***	0,09691*	0,85363***
Swedbank A	-0,07192***	-0,05677***	-0,25201***	0,66963***	1,05345***
Swedish Match	-0,04593***	-0,04268***	-0,03891	0,30121	-0,24459
TDC	-0,04573***	-0,04310***	-0,19754***	-0,03672	0,67472***
TeliaSonera	-0,05769***	-0,04947***	-0,27580***	-0,26027	-0,22509
UPM Kymmene	-0,06170***	-0,05605***	-0,06204***	0,26708***	0,56410***
Vestas Windsystems	-0,09327***	-0,08374***	-0,27714***	0,53027***	0,82006
Volvo B	-0,06075***	-0,04193***	-0,16147***	0,44814***	0,48868***
Average	-0,05642	-0,04787	-0,15562	0,26980	0,47725
OMX	-0,04381***	-0,03005***	-0,18956***	0,21025***	0,22440**
EUROSTOXX	-0,04693***	-0,02279***	-0,20440***	0,35178***	0,27714***

VaR 50%	Unconditional	Conditional			
	α	α	β1 (volatility)	β2 (S&P500)	β3 (euribor)
A.P Möller Maersk	0,00000	0,00000	-0,10378***	0,29929***	-0,00611
Assa Aboly B	0,00000	0,00022	-0,11753***	0,35640***	-0,03350
Astra Zeneca	0,00000	0,00000	-0,06262***	0,08970***	-0,00186
Atlas Copco A	0,00000	0,00023	-0,14446***	0,44770***	0,04714
Atlas Copco B	0,00000	0,00037	-0,15170***	0,46288***	0,03686
Autoliv SDB	0,00000	0,00000	-0,10300***	0,23361***	0,01608
Carlsberg B	0,00000	0,00000	-0,06632***	0,18258***	0,03790
Coloplast B	0,00000	0,00013	-0,04435***	0,09116**	0,00398
Danske Bank	0,00000	0,00000	-0,10371***	0,22756***	-0,00689
Electrolux B	0,00000	0,00000	-0,11230***	0,42860***	-0,03379
Elekta B	0,00000	0,00018	-0,07407***	0,15249***	0,00281
Ericsson B	0,00000	0,00000	-0,11579***	0,36465***	-0,01140
Fortum	0,00000	0,00028	-0,07327***	0,17327***	0,00012
Getinge	0,00000	0,00023	-0,07620***	0,22617***	-0,01369
H&M B	0,00000	0,00016	-0,08798***	0,23053***	-0,02767
Investor B	0,00000	0,00021	-0,12295***	0,32236***	0,03543
Kinnevik B	0,00000	0,00039	-0,10761***	0,32328***	0,02275
Kone B	0,00000	0,00027	-0,09286***	0,18824***	-0,00623
Nokia	0,00000	0,00000	-0,15818***	0,37302***	0,03243
Nokian Renkaat	0,00000	0,00043	-0,11671***	0,30430***	0,02271
Nordea Bank	0,00000	0,00000	-0,13144***	0,35805***	0,03570
Novo nordisk B	0,00000	0,00024	-0,04683***	0,11285***	-0,07148
Sampo A	0,00000	0,00028	-0,10051***	0,27724***	0,00016
Sandvik	0,00000	0,00028	-0,13330***	0,40852***	0,04300
SCA B	0,00000	0,00000	-0,08206***	0,22632***	-0,01397
Scania B	0,00000	0,00000	-0,11554***	0,36302***	0,08564
SEB A	0,00000	0,00000	-0,13336***	0,51539***	0,03527
Skanska B	0,00000	0,00029	-0,10389***	0,39708***	0,01408
SKF B	0,00000	0,00000	-0,11646***	0,43378***	0,04041
Stora Enso R	0,00000	0,00000	-0,14373***	0,36345***	0,06660
Swedbank A	0,00000	0,00038	-0,11912***	0,40526***	0,06721
Swedish Match	0,00000	0,00012	-0,04770***	0,11582***	-0,02454
TDC	0,00000	0,00000	-0,03288***	0,06113**	0,01340
TeliaSonera	0,00000	0,00000	-0,09011***	0,25870***	0,00237
UPM Kymmene	0,00000	0,00000	-0,12492***	0,29679***	0,08639
Vestas Windsystems	0,00000	0,00000	-0,16184***	0,20578***	0,04962
Volvo B	0,00000	0,00024	-0,13139***	0,44667***	0,05012
Average	0,00000	0,00013	-0,10407	0,28983	0,01614
OMX	0,00033	0,00023	-0,12369***	0,35626***	0,00403
EUROSTOXX	0,00000	0,00000	-0,13678***	0,38389***	0,02855

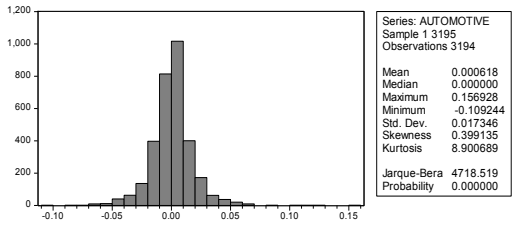
CoVaR 1%	Unconditional		Conditional				
	α	β1	α	βi (stock)	β2 (volatility)	β3(S&P500)	β4 (euribor)
A.P Möller Maersk	-0,03507***	0,37272***	-0,02893***	0,14816***	-0,15590***	0,17151***	0,13626
Assa Aboly B	-0,03255***	0,43731***	-0,02610***	0,30920***	-0,15127***	0,12683***	0,21284**
Astra Zeneca	-0,04222***	0,27920***	-0,03071***	0,13207**	-0,17224***	0,18480***	0,27573**
Atlas Copco A	-0,03070***	0,49490***	-0,02657***	0,28435***	-0,13969***	0,08656***	0,09366
Atlas Copco B	-0,03106***	0,49900***	-0,02669***	0,30535***	-0,12993***	0,07678***	0,13620
Autoliv SDB	-0,03862***	0,45510***	-0,02900***	0,23277***	-0,16873***	0,25046***	0,20621
Carlsberg B	-0,03675***	0,32570***	-0,02955***	0,14213***	-0,18510***	0,12524	0,15330
Coloplast B	-0,04132***	0,33931***	-0,02854***	0,21293***	-0,18714***	0,09809***	0,25941***
Danske Bank	-0,03550***	0,38188***	-0,02834***	0,22764***	-0,13941***	0,20834***	0,20103***
Electrolux B	-0,03448***	0,32942***	-0,02762***	0,17919***	-0,15847***	0,14096***	0,16632
Elekta B	-0,04119***	0,34219***	-0,02934***	0,16060***	-0,16038***	0,18723***	0,25633***
Ericsson B	-0,03333***	0,29798***	-0,02569***	0,22407***	-0,14364***	0,18769***	0,25121***
Fortum	-0,03644***	0,41562***	-0,02907***	0,22418***	-0,16845***	0,10725***	0,26346**
Getinge	-0,03675***	0,51733***	-0,02968***	0,19358**	-0,17296***	0,14731***	0,21790*
H&M B	-0,03339***	0,52154***	-0,02637***	0,30833***	-0,14824***	0,17544***	0,10956
Investor B	-0,02633***	0,72658***	-0,02341***	0,52960***	-0,09138***	0,06480***	0,15184*
Kinnevik B	-0,03572***	0,43322***	-0,02889***	0,19859***	-0,18639***	0,15717***	0,20293*
Kone B	-0,03649***	0,53214***	-0,02857***	0,32740***	-0,13448***	0,17076***	0,36224***
Nokia	-0,03001***	0,36349***	-0,02361***	0,22589***	-0,13551***	0,16386***	0,13718
Nokian Renkaat	-0,03808***	0,29908***	-0,02835***	0,16828***	-0,17071***	0,14182***	0,13244
Nordea Bank	-0,03064***	0,51154***	-0,02455***	0,35282***	-0,12852***	0,18107***	0,14536**
Novo nordisk B	-0,04137***	0,39555***	-0,02945***	0,26326***	-0,14633***	0,21658***	0,39961***
Sampo A	-0,03500***	0,45733***	-0,02810***	0,24361**	-0,15612**	0,09653	0,17205*
Sandvik	-0,03102***	0,50654***	-0,02638***	0,26198***	-0,16422***	0,10734*	0,18152**
SCA B	-0,03675***	0,52213***	-0,02843***	0,32271***	-0,15247***	0,13566***	0,28986***
Scania B	-0,03487***	0,37013***	-0,02891***	0,13606***	-0,18363***	0,13659***	0,21997**
SEB A	-0,03060***	0,36752***	-0,02635***	0,21620***	-0,15482***	0,07757***	0,12566
Skanska B	-0,03201***	0,55292***	-0,02585***	0,36911***	-0,13292***	0,15835***	0,08765
SKF B	-0,03183***	0,50211***	-0,02638***	0,31579***	-0,14873***	0,13709***	0,15433*
Stora Enso R	-0,03551***	0,38915***	-0,02652***	0,25228***	-0,14024***	0,13093***	0,24250***
Swedbank A	-0,03492***	0,38128***	-0,02932***	0,19919***	-0,15203***	0,07880***	0,20214
Swedish Match	-0,04074***	0,39190***	-0,03042***	0,07868	-0,19746***	0,18069***	0,19265*
TDC	-0,04080***	0,27987***	-0,02913***	0,17346***	-0,17609***	0,20373***	0,24026***
TeliaSonera	-0,03456***	0,45543***	-0,02741***	0,31279***	-0,13726***	0,14839***	0,27171**
UPM Kymmene	-0,03277***	0,52115***	-0,02750***	0,31146***	-0,13686***	0,12619***	0,29366***
Vestas Windsystems	-0,03681***	0,19871***	-0,02801***	0,10117***	-0,15328***	0,21705***	0,13266***
Volvo B	-0,03126***	0,44354***	-0,02625***	0,29046***	-0,15700***	0,06397	0,15323**
Average	-0,03507	0,42191	-0,02767	0,24150	-0,15454	0,14512	0,20083
OMX	-0,02197***	0,83435***	-0,02243***	0,83213***	-0,02132***	-0,04701***	-0,15952***
EUROSTOXX	-0,02195***	0,94516***	-0,01705***	0,54456***	-0,10431	0,20418	0,22820

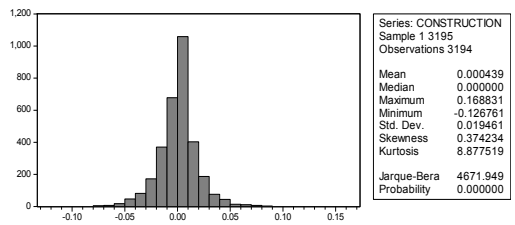
CoVaR 50%	Unconditional		Conditional				
	α	β1	α	βi (stock)	β2 (volatility)	32 (S&P500)	β4 (euribor)
A.P Möller Maersk	0,00000	0,39324***	0,00022	0,23835***	-0,09562***	0,29439***	-0,00512
Assa Aboly B	0,00000	0,47144***	0,00000	0,29464***	-0,08844***	0,24263***	0,00000
Astra Zeneca	0,00000	0,31754***	0,00024	0,12053***	-0,11555***	0,35089***	-0,00270
Atlas Copco A	0,00000	0,50976***	0,00000	0,34974***	-0,06884***	0,21111***	-0,00108
Atlas Copco B	0,00000	0,47660***	0,00000	0,32213***	-0,07319***	0,20722***	0,00486
Autoliv SDB	0,00000	0,45263***	0,00031**	0,25286***	-0,09269***	0,29951***	-0,00082
Carlsberg B	0,00035*	0,31390***	0,00012	0,16913***	-0,10890***	0,33160***	0,04459**
Coloplast B	0,00020	0,48716***	0,00000	0,13504***	-0,11715***	0,33450***	-0,00267***
Danske Bank	0,00026	0,43216***	0,00025	0,24299***	-0,09459***	0,30880***	0,01249
Electrolux B	0,00000	0,42688***	0,00014	0,24722***	-0,08976***	0,27343***	-0,00333
Elekta B	0,00000	0,19513***	0,00023	0,10850***	-0,11287***	0,35148***	0,01083
Ericsson B	0,00000	0,36133***	0,00021	0,23070***	-0,09514***	0,25931***	0,00286
Fortum	0,00000	0,32550***	0,00016	0,16140***	-0,10949***	0,33576***	0,01693
Getinge	0,00000	0,37619***	0,00000	0,20173***	-0,10430***	0,33149***	-0,00567
H&M B	0,00000	0,58114***	0,00018	0,32914***	-0,08989***	0,32810***	0,00727
Investor B	0,00000	0,68472***	0,00000	0,49923***	-0,05715***	0,20537***	-0,02370
Kinnevik B	0,00000	0,43807***	0,00000	0,25187***	-0,09446***	0,28587***	-0,03239
Kone B	0,00000	0,42684***	0,00000	0,23766***	-0,09602***	0,30133***	-0,00611
Nokia	0,00020	0,42872***	0,00012	0,27743***	-0,08245***	0,25222***	0,02825
Nokian Renkaat	0,00000	0,29927***	0,00000	0,15084***	-0,09946***	0,34870***	-0,00126
Nordea Bank	0,00000	0,56535***	0,00000	0,38580***	-0,07473***	0,19595***	-0,01711
Novo nordisk B	0,00000	0,27335***	0,00000	0,17214***	-0,11935***	0,33029***	-0,00345
Sampo A	0,00000	0,52528***	0,00012	0,29570***	-0,09438***	0,26837***	0,00939
Sandvik	0,00000	0,50347***	0,00000	0,34051***	-0,07604***	0,19659***	-0,00456
SCA B	0,00000	0,58891***	0,00020	0,34278***	-0,09284***	0,27837***	0,00802
Scania B	0,00000	0,47404***	0,00000	0,29458***	-0,08653***	0,25217***	-0,01089
SEB A	0,00000	0,47234***	0,00016	0,30617***	-0,07952***	0,21413***	-0,01946
Skanska B	0,00000	0,56557***	0,00000	0,35716***	-0,07981***	0,24786***	0,00336
SKF B	0,00000	0,53490***	0,00011	0,34745***	-0,07647***	0,21233***	-0,02139
Stora Enso R	0,00027	0,42344***	0,00031**	0,26070***	-0,08269***	0,26588***	-0,00395
Swedbank A	0,00000	0,44587***	0,00014	0,26597***	-0,08843***	0,24206***	-0,01961
Swedish Match	0,00019	0,21626***	0,00024	0,09457***	-0,11596***	0,35641***	0,03043*
TDC	0,00011	0,27145***	0,00000	0,15341***	-0,11888***	0,33106***	-0,00692
TeliaSonera	0,00000	0,46739***	0,00013	0,26914***	-0,09362***	0,31647***	0,02168
UPM Kymmene	0,00029*	0,46202***	0,00026*	0,27473***	-0,08696***	0,26948***	-0,02335
Vestas Windsystems	0,00000	0,17603***	0,00000	0,09300***	-0,10733***	0,33022***	-0,00222
Volvo B	0,00000	0,50668***	0,00015	0,33688***	-0,07376***	0,21566***	-0,00536
Average	0,00005	0,42893	0,00011	0,25437	-0,09279	0,28046	-0,00060
OMX	0,00000	0,87295***	0,00000	0,81924***	-0,01041***	0,03981**	-0,01755
EUROSTOXX	0,00000	0,82625***	-0,00013	0,54376***	-0,07220***	0,18870***	0,01883

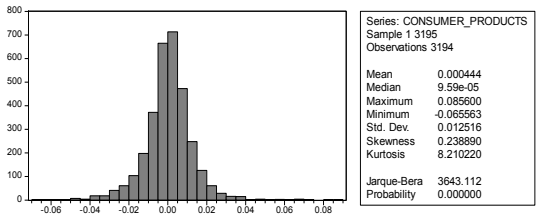
Appendix 3 Descriptive statistics of returns data (firm specific)

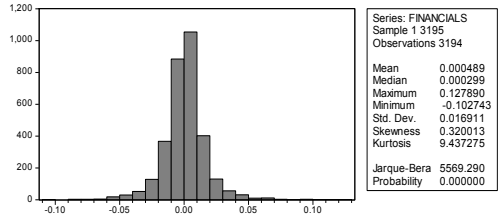
Stock	Mean	St. Dev	Max	Min	Kurtosis	Skewness
AUTOLIV SDB	0,00053180	0,01880287	0,13398693	-0,15945946	6,12554780	0,17987263
ASSA ABLOY 'B'	0,00048509	0,02130778	0,17006803	-0,16766467	6,20590423	0,19348401
ATLAS COPCO 'A'	0,00082139	0,02251783	0,15512979	-0,13401177	4,27906559	0,31571545
ATLAS COPCO 'B'	0,00085496	0,02360486	0,15240578	-0,13906378	3,89690182	0,34179017
ASTRAZENECA (OME)	0,00008006	0,01563685	0,12859560	-0,11756168	6,78329970	0,00924778
CARLSBERG 'B'	0,00043212	0,02064207	0,15657895	-0,17480035	10,08648786	-0,07012999
COLOPLAST 'B'	0,00077125	0,01557043	0,13833992	-0,16876574	10,32306549	0,20210832
DANSKE BANK	0,00028192	0,02099931	0,14989194	-0,15787763	6,01008848	0,19144955
ELEKTA 'B'	0,00103319	0,02156114	0,14923707	-0,15217391	4,59340943	0,05134615
ELECTROLUX 'B'	0,00046629	0,02351379	0,21146953	-0,18778142	7,38026511	0,32481519
ERICSSON 'B'	0,00014158	0,02873761	0,25000000	-0,23958655	11,16727462	0,15053110
FORTUM	0,00064206	0,01795081	0,14601227	-0,11381074	6,58611140	0,17266213
GETINGE	0,00062625	0,01810193	0,12307692	-0,21443919	10,19869725	-0,46819171
H & M 'B'	0,00043049	0,01663935	0,12962963	-0,10765550	5,42423074	0,25758616
INVESTOR 'B'	0,00038042	0,01770171	0,14615385	-0,10317460	5,02195363	0,24370370
KINNEVIK 'B'	0,00070825	0,02155224	0,16197183	-0,16384181	7,25084626	0,00804729
KONE 'B'	0,00098953	0,01843374	0,12121212	-0,12121212	3,97159870	0,22366310
A P M-MAERSK 'B'	0,00052231	0,02141576	0,26324615	-0,12993039	11,45201867	0,79662523
NORDEA BANK	0,00046356	0,02170132	0,16082005	-0,11497249	6,43225980	0,62760738
NOKIA	-0,00013982	0,02778473	0,34121622	-0,17567568	11,43403826	0,20955442
NOVO NORDISK 'B'	0,00077655	0,01766192	0,18155620	-0,21354934	15,97266561	-0,43729374
NOKIAN RENKAAT	0,00098238	0,02518959	0,24612920	-0,21674877	9,94824685	0,17495313
SAMPO 'A'	0,00061993	0,01811629	0,12801484	-0,16666667	8,37368981	-0,21386091
SANDVIK	0,00047036	0,02167420	0,14114833	-0,14869888	4,32596721	0,18709100
SCA 'B'	0,00034731	0,01624885	0,12053571	-0,12141280	6,72945387	0,33654809
SCANIA 'B'	0,00070487	0,02199708	0,31864407	-0,11573343	16,88694774	1,27260170
SEB 'A'	0,00052051	0,02600612	0,26130653	-0,20006081	11,50553478	0,62033033
SKANSKA 'B'	0,00043920	0,01945785	0,16883117	-0,12676056	5,88861163	0,37440941
SKF 'B'	0,00064594	0,02097561	0,13427562	-0,09682312	3,91849951	0,48576448
STORA ENSO 'R'	0,00006574	0,02279786	0,15711645	-0,10730253	3,30694604	0,35018705
SWEDBANK 'A'	0,00044958	0,02447306	0,18955399	-0,18565956	9,07558780	0,19196424
SWEDISH MATCH	0,00054552	0,01592095	0,10874704	-0,09547739	3,78631747	0,14651965
TDC	0,00015025	0,01887396	0,16414435	-0,52948718	200,88826461	-6,62028503
TELIASONERA	0,00020723	0,01927853	0,21537046	-0,12907410	10,72921069	0,35584847
UPM-KYMMENE	0,00010245	0,02143545	0,12005857	-0,10020450	3,15127658	0,11230062
VOLVO 'B'	0,00061757	0,02219317	0,16332378	-0,14252874	3,92987673	0,16959992
VESTAS WINDSYST	0,00070048	0,03692302	0,44398196	-0,31656938	14,31458777	0,49744994

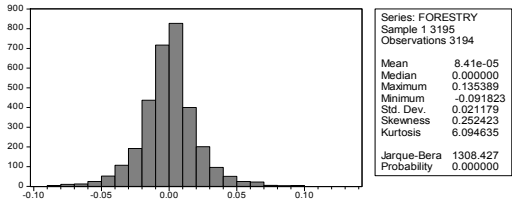
Appendix 4 Jarque-Bera statistics for normality of sector returns and their empirical distributions; *Automotive, Construction, Consumer products, Financials, Forestry, Health care, Telecommunications, Transportation, Utility* and *Manufacturing.*

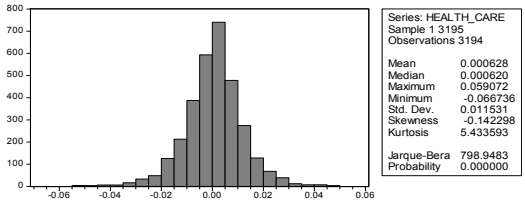


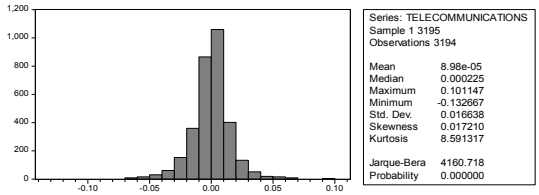


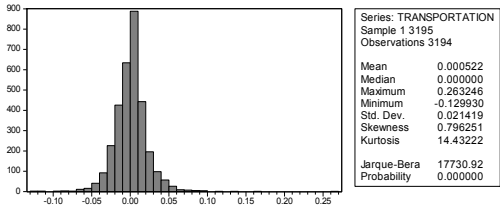


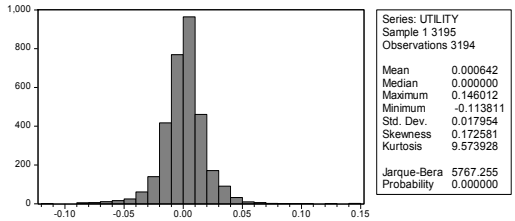


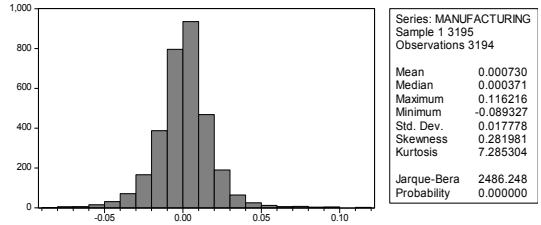












Appendix 5 Augmented Dickey-Fuller test for stationarity of macro variables; *Volatility of EuroStoxx50*, *S&P500* and *3M Euribor interest rate*, levels and first-differences tested, with constant and linear trend, constant and neither included in the underlying test equation. Automatic selection of lags.

		Constant, Linear trend	Constant	None
EuroStoxx50 Volatility	p-value	0,02020	0,00400	0.1175
	BIC	4,01396	4,01150	4,01255
d-EuroStoxx50 Volatility	p-value	0,00000	0,00000	0,00000
	BIC	-2,84723	-2,84974	-2,85139
S&P	p-value	0,86360	0,91930	0,90700
	BIC	8,10332	8,10934	8,09949
d-S&P	p-value	0,00000	0,00010	0,00010
	BIC	-5,89583	-5,89801	-5,90012
Euribor3M	p-value	0,87660	0,79340	0,17870
	BIC	-6,46209	-6,46426	-6,46678
d-Euribor3M	p-value	0,00000	0,00000	0,00000
	BIC	-7,53848	-7,54077	-7,54251

Appendix 6 Conditional (averages) and unconditional firm specific numerical estimates of 50%-VaR, 50%-CoVaR, 1%-VaR, 1%-CoVaR and ΔCoVaR, estimated by using estimates in appendix 2 and according to equations 2, 4, 6, 7, 9, 11, 12, 13, 15, 17, 19-21.

Conditional estimation i/system	VaR 50 %	CoVaR 50%	VaR 1%	CoVaR 1%	ΔCoVaR
A P MOLLER -MAERSK 'B'	-0,0000811	0,0020899	-0,0442550	-0,0357801	-0,0378701
ASSA ABLOY 'B'	0,0001482	-0,0000321	-0,0467976	-0,0409167	-0,0408847
ASTRAZENECA (OME)	-0,0000715	0,0001413	-0,0422593	-0,0367036	-0,0368449
ATLAS COPCO 'A'	0,0000847	-0,0000234	-0,0439231	-0,0391199	-0,0390966
ATLAS COPCO 'B'	0,0002257	0,0000081	-0,0455147	-0,0408594	-0,0408675
AUTOLIV SDB	-0,0001111	0,0002177	-0,0437483	-0,0395214	-0,0397391
CARLSBERG 'B'	-0,0000837	-0,0000165	-0,0528445	-0,0374151	-0,0373986
COLOPLAST 'B'	0,0000830	-0,0000841	-0,0356545	-0,0365779	-0,0364937
DANSKE BANK	-0,0000972	0,0001470	-0,0532581	-0,0407700	-0,0409170
ELECTROLUX 'B'	-0,0000439	0,0000640	-0,0520300	-0,0372662	-0,0373303
ELEKTA 'B'	0,0001067	0,0001430	-0,0495215	-0,0376716	-0,0378146
ERICSSON 'B'	-0,0000800	0,0001086	-0,0714675	-0,0420502	-0,0421588
FORTUM	0,0002067	0,0000978	-0,0469611	-0,0400129	-0,0401107
GETINGE	0,0001765	-0,0079950	-0,0392837	-0,0376669	-0,0296719
HENNES & MAURITZ 'B'	0,0000965	-0,0067269	-0,0387552	-0,0385739	-0,0318470
INVESTOR 'B'	0,0000769	0,0000177	-0,0350403	-0,0422273	-0,0422450
KINNEVIK 'B'	0,0002882	0,0000210	-0,0500832	-0,0392201	-0,0392412
KONE 'B'	0,0001711	-0,0000283	-0,0423639	-0,0428596	-0,0428312
NOKIA	-0,0001729	-0,0000116	-0,0725184	-0,0402507	-0,0402391
NOKIAN RENKAAT	0,0003051	-0,0000205	-0,0541379	-0,0377754	-0,0377549
NORDEA BANK	-0,0001386	-0,0001074	-0,0493239	-0,0422045	-0,0420971
NOVO NORDISK 'B'	0,0002442	-0,0000459	-0,0426222	-0,0411200	-0,0410741
SAMPO 'A'	0,0001932	0,0000908	-0,0390060	-0,0379377	-0,0380285
SANDVIK	0,0001422	-0,0000163	-0,0452823	-0,0385910	-0,0385747
SCA 'B'	-0,0000600	0,0000967	-0,0357968	-0,0403843	-0,0404811
SCANIA 'B'	-0,0001492	-0,0001069	-0,0469432	-0,0357000	-0,0355932
SEB 'A'	-0,0001044	0,0000769	-0,0549867	-0,0385418	-0,0386187
SKANSKA 'B'	0,0002212	0,0000150	-0,0420625	-0,0416032	-0,0416182
SKF 'B'	-0,0001018	0,0000290	-0,0432572	-0,0403452	-0,0403742
STORA ENSO 'R'	-0,0001778	0,0002052	-0,0529525	-0,0402258	-0,0404310
SWEDBANK 'A'	0,0002464	0,0001467	-0,0577425	-0,0401715	-0,0403181
SWEDISH MATCH	0,0000971	0,0001321	-0,0424947	-0,0341506	-0,0342827
TDC	-0,0000445	-0,0001026	-0,0438896	-0,0371308	-0,0370282
TELIASONERA	-0,0000762	0,0000248	-0,0497836	-0,0433467	-0,0433715
UPM-KYMMENE	-0,0001194	0,0001756	-0,0564868	-0,0454796	-0,0456552
VESTAS WINDSYSTEMS	-0,0002297	-0,0001033	-0,0846220	-0,0368456	-0,0367422
VOLVO 'B'	0,0001159	0,0001288	-0,0424213	-0,0388958	-0,0390246
OMXNORDIC	0,0001232	0,0001071	-0,0304477	-0,0339060	-0,0340131
EUROSTOXX50	-0,0001355	-0,0002801	-0,0232160	-0,0416795	-0,0413994

Unconditional estimation i/system	VaR 50%	CoVaR 50%	VaR 1%	CoVaR 1%	ΔCoVaR
A P MOLLER - MAERSK 'B'	0,000000	0,000000	-0,053191	-0,054892	-0,054892
ASSA ABLOY 'B'	0,000000	0,000000	-0,054313	-0,056300	-0,056300
ASTRAZENECA (OME)	0,000000	0,000000	-0,043672	-0,054411	-0,054411
ATLAS COPCO 'A'	0,000000	0,000000	-0,054618	-0,057726	-0,057726
ATLAS COPCO 'B'	0,000000	0,000000	-0,058824	-0,060415	-0,060415
AUTOLIV SDB	0,000000	0,000000	-0,047619	-0,060291	-0,060291
CARLSBERG 'B'	0,000000	0,000000	-0,055440	-0,054810	-0,054810
COLOPLAST 'B'	0,000000	0,000000	-0,038345	-0,054328	-0,054328
DANSKE BANK	0,000000	0,000000	-0,061220	-0,058880	-0,058880
ELECTROLUX 'B'	0,000000	0,000000	-0,066202	-0,056287	-0,056287
ELEKTA 'B'	0,000000	0,000000	-0,556520	-0,231624	-0,231624
ERICSSON 'B'	0,000000	0,000000	-0,080311	-0,057277	-0,057277
FORTUM	0,000000	0,000000	-0,052962	-0,058451	-0,058451
GETINGE	0,000000	0,000000	-0,044145	-0,059583	-0,059583
HENNES & MAURITZ 'B'	0,000000	0,000000	-0,045521	-0,057129	-0,057129
INVESTOR 'B'	0,000000	0,000000	-0,047198	-0,060623	-0,060623
KINNEVIK 'B'	0,000000	0,000000	-0,060498	-0,061927	-0,061927
KONE 'B'	0,000000	0,000000	-0,047676	-0,061855	-0,061855
NOKIA	0,000000	0,000000	-0,078947	-0,058710	-0,058710
NOKIAN RENKAAT	0,000000	0,000000	-0,061988	-0,056620	-0,056620
NORDEA BANK	0,000000	0,000000	-0,058539	-0,060584	-0,060584
NOVO NORDISK 'B'	0,000000	0,000000	-0,046332	-0,059701	-0,059701
SAMPO 'A'	0,000000	0,000000	-0,048059	-0,056977	-0,056977
SANDVIK	0,000000	0,000000	-0,055319	-0,059044	-0,059044
SCA 'B'	0,000000	0,000000	-0,040816	-0,058062	-0,058062
SCANIA 'B'	0,000000	0,000000	-0,059028	-0,056716	-0,056716
SEB 'A'	0,000000	0,000000	-0,068815	-0,055888	-0,055888
SKANSKA 'B'	0,000000	0,000000	-0,052265	-0,060909	-0,060909
SKF 'B'	0,000000	0,000000	-0,051499	-0,057692	-0,057692
STORA ENSO 'R'	0,000000	0,000000	-0,061674	-0,059508	-0,059508
SWEDBANK 'A'	0,000000	0,000000	-0,071924	-0,062342	-0,062342
SWEDISH MATCH	0,000000	0,000000	-0,045929	-0,058742	-0,058742
TDC	0,000000	0,000000	-0,045732	-0,053603	-0,053603
TELIASONERA	0,000000	0,000000	-0,057692	-0,060830	-0,060830
UPM-KYMMENE	0,000000	0,000000	-0,617040	-0,354336	-0,354336
VESTAS WINDSYSTEMS	0,000000	0,000000	-0,093266	-0,055340	-0,055340
VOLVO 'B'	0,000000	0,000000	-0,060748	-0,058201	-0,058493
OMXNORDIC	0,000334	0,000291	-0,043810	-0,058521	-0,058521
EUROSTOXX50	0,000000	0,000000	-0,046932	-0,066312	-0,066312

Appendix 7 Relevant coefficient estimates for 1% and 50% conditional CoVaR estimations of banks; Bank *j* in bold on the top left hand side is the dependent variable, regressed on the independent variable, bank *j*, in italics. 22 regressions performed.

	q=1%		*q=50%*	
SEB	α	β	α	β
Danske Bank	-0,05886***	0,74516***	0,00000	0,57761***
Swedbank	-0,04341***	0,78481***	0,00000	0,83665***
Nordea	-0,04740***	1,03201***	0,00000	0,84767***
Danske Bank	α	β	α	β
SEB	-0,04963***	0,33846***	0,00000	0,41413***
Swedbank	-0,05006***	0,42182***	0,00000	0,43554***
Nordea	-0,05093***	0,47484***	0,00000	0,48349***
Swedbank	α	β	α	β
SEB	-0,04685***	0,68638***	0,00000	0,72947***
Danske Bank	-0,06166***	0,61417***	0,00000	0,53298***
Nordea	-0,05279***	0,84210***	0,00000	0,70490***
Nordea	α	β	α	β
SEB	-0,04179***	0,49338***	0,00000	0,64806***
Danske Bank	-0,05229***	0,40221***	0,00000	0,50913***
Swedbank	-0,04584***	0,50485***	0,00000	0,62176***