Implementation of CoVaR,

A Measure for Systemic Risk

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August, 2012

Abstract

In recent years we have witnessed how distress can spread quickly through the financial system and threaten financial stability. Hence there has been increased focus on developing systemic risk indicators that can be used by central banks and others as a monitoring tool. For Sveriges Riksbank it is of great value to be able to quantify the risks that can threaten the Swedish financial system. CoVaR is a systemic risk measure implemented here with that with that purpose. CoVaR, which stands for conditional Value at Risk, measures a financial institutions contribution to systemic risk and its contribution to the risk of other financial institutions. The conclusion is that CoVaR can together with other systemic risk indicators help get a better understanding of the risks threatening the stability of the Swedish financial system.

Acknowledgements

I would like to thank my supervisor Tobias Rydén at KTH Royal Institute of Technology for his guidance and helpful comments, Olof Sandstedt and Martin W. Johansson at Sveriges Riksbank for their mentoring and the opportunity to work on this project. I would also like to thank my family and friends for their support during the course of this work.

Stockholm, August 2012

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1. Introduction

In recent years we have witnessed how distress can spread quickly through the financial system and threaten financial stability. A systemic crisis that disrupts the stability of the financial system can have serious consequences and large costs for the whole economy and the society. Sveriges Riksbank is responsible for promoting financial stability in Sweden and hence it is a central component of the Riksbank's activities to follow and analyse systemic risk.

The Group of Ten[1] has defined Systemic Risk by:

> "Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly [sic] about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. Systemic risk events can be sudden and unexpected, or the likelihood of their occurrence can build up through time in the absence of appropriate policy responses. The adverse real economic effects from systemic problems are generally seen as arising from disruptions to the payment system, to credit flows, and from the destruction of asset values." [1]

The financial crisis in 2008 has put an increased emphasis on analysing systemic risk and developing systemic risk indicators that can be used by central banks and others as a monitoring tool. For the Riksbank it is of great value to be able to quantify the systemic risk that can threaten the Swedish banking system.

CoVaR is a systemic risk measure proposed by Brunnermeier and Adrian [2]. CoVaR measures a financial institutions contribution to systemic risk and its contribution to the risk of other financial institutions. CoVaR stands for conditional Value at Risk, i.e. it indicates the Value at Risk for a financial institution conditional on a certain scenario. In this thesis the CoVaR measure is used to estimate the systemic risk that can disrupt financial stability in the Swedish banking system.

Chapter 2 covers the theoretical background needed to understand and apply the CoVaR model. In Chapter 3 the CoVaR model is explained. Chapter 4 describes the data used as an input to model. The results are presented in Chapter 5. The CoVaR estimation is first evaluated for the Swedish banking system in its isolation and then as a part of a larger international banking system. The main focus is on the Swedish banking system and how it can be affected by risk events in individual banks. Finally in Chapter 6 conclusions are drawn.

[1] The Group of Ten (G-10) refers to the group of countries that have agreed to participate in the General Arrangements to Borrow (GAB), a supplementary borrowing arrangement that can be invoked if the IMF's resources are estimated to be below member's needs (http://www.imf.org/external/np/exr/facts/groups.htm).

2 Theoretical background

2.1 Quantile Regression

Quantile regression is an efficient way to estimate CoVaR and is used here. Quantile regression models the relation between a predictor variable (or a set of predictor variables) and specific quantiles of the response variable [3]. In Ordinary Least Squares (OLS) regression, a regression coefficient estimates the change in the mean of the response variable produced by a one unit change in the predictor variable, keeping other predictor variables fixed [4]. However, a quantile regression coefficient estimates the change in a specified quantile of the response variable produced by a one unit change in the predictor variable. This enables comparison of how different quantiles of the response variable may be affected by the predictor variable. When estimating CoVaR the focus is on a specific low quantile of a distribution and hence it is convenient to use quantile regression here.

2.1.1 Quantiles

Quantile $\tau \in [0,1]$ of distribution F with distribution function $F(y) = P(Y \leq y)$ is defined by:

(1) $$F^{-1}(\tau) = \inf\{y: F(y) \geq \tau\}.$$

Now, if a loss function is defined by

(2) $$\rho_\tau(y) = y\big(\tau - \mathrm{I}(y < 0)\big),$$

then the quantile τ can be found by estimating $\hat{y}$ that minimizes the expected loss of $(Y - \hat{y})$, i.e. by minimizing

(3) $$E\big(\rho_\tau(Y - \hat{y})\big) = \int \rho_\tau(y - \hat{y}) = (\tau - 1)\int_{-\infty}^{\hat{y}} (y - \hat{y})dF(y) + \tau\int_{\hat{y}}^{\infty} (y - \hat{y})dF(y)$$

Differentiating and setting equal to zero,

(4) $$0 = (\tau - 1)\int_{-\infty}^{\hat{y}} dF(y) + \tau\int_{\hat{y}}^{\infty} dF(y) = F(\hat{y}) - \tau,$$

gives $F(\hat{y}) = \tau$ and finally $\hat{y} = F^{-1}(\tau)$. By definition (1) above, $\hat{y}$ is the τ quantile of distribution F.

When F is an empirical distribution, the quantile τ can in accordance to (3) and (4) be estimated by minimizing the following equation with respect to $\hat{y}$.

(5) $$E\big(\rho_\tau(Y - \hat{y})\big) \approx \frac{1}{n}\sum_{i=1}^{n} \rho_\tau(y_i - \hat{y})$$

2.1.2 Quantile regression

If one has a conditional quantile function of the distribution of Y given the distribution of X defined by

(6) $$Q_y(\tau|\mathrm{x}) = \mathbf{x}^T\beta_\tau$$

for a specific quantile τ, then by using the derivation above one can minimize the following equation

(7) $$\frac{1}{n}\sum_{i=1}^{n}\rho_\tau(y_i - \mathbf{x}^T\beta_\tau)$$

with respect to β_τ to get an estimator $\hat{\beta}_\tau$.The regression coefficients vector $\hat{\beta}_\tau$ describes how much $Q_y(\tau|\mathrm{x})$ changes due to a one unit change in one of the predictor variables contained in vector $\mathbf{x}^T$. Equation (7) can be rewritten and solved as a linear programming problem by using 2n slack variables (u^+, u^-) to represent the positive and negative vector residuals,

(8) $$\min_{(\beta,u,v)\epsilon\mathbb{R}^P\times\mathbb{R}_+^{2n}}\{\tau 1_n^T u^+ + (1-\tau)1_n^T u^- | \boldsymbol{X}\beta + u^+ - u^- = y\},$$

where X is the $n \times p$ regression matrix of p predictive variables and the solution $\hat{\beta}_\tau$ is an $n \times 1$ vector of the τ-quantile regression parameter estimates. This linear program can be solved using the Simplex method or interior point methods. [3]

Koenker and Basset first presented quantile regression in 1978 [5] and in 2005 Koenker published a book on covering quantile regression in more detail. [3].

2.1.3 Example

An example where quantile regression was useful was in a study that was done to investigate how birth weight of infants might be affected by various predictor variables. Low birth weight has been linked with many health problems and therefore it was of interest to investigate the impact on the lower quantiles of the birth weight distribution. A study on this, based on real data was carried out by Koenker and Hallock in 2001 [6]. Among predictor variables were prenatal visits, education and marital status of the mother.

When OLS regression is used the results estimate the effect of the predictor variables on the conditional mean of birth weights. That however might not indicate the effects on the lower tail of the birth weight distribution. Quantile regression provides more information about the effects of the predictor variables on different quantiles.

Below in figure 1 is a plot of one of those regression coefficients, for the “No prenatal” variable. The solid line with dots represents the β estimate as a function of the quantiles. The grey area is a 90% confidence interval for the β values. The dashed horizontal line represents the result from OLS regression and the dotted lines that lie above and below it is the 90% confidence interval. The “No Prenatal” variable has value 0 if the mother had a prenatal care from the start and it has value 1 if the mother had no prenatal care. The result from OLS regression (the red line) indicates that when a mother has no prenatal care the birth weight of the infant is on average 190 gram lower than for infants born to mothers that had prenatal visits from the start. The quantile regression results indicate different relation between birth weight of infants and prenatal care depending on the quantiles. As an example the 10% quantile of birth weight for infants born to mother who had no prenatal care is around 300 grams lower than for infants born to mothers that had prenatal visits from the start. The results indicate that the effect of no prenatal care has a larger negative effect on infants' birth weight in the lower quantiles compared to the effect on the mean weight.

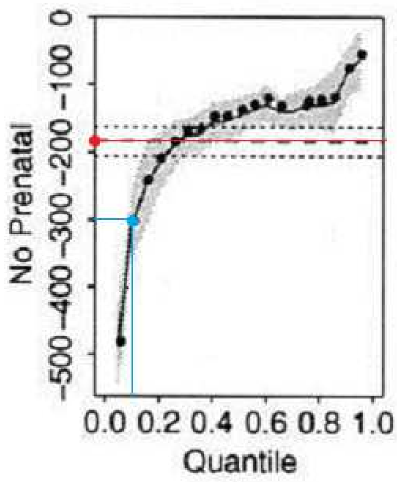


Figure 1

2.2 Value at Risk (VaR)

Value at Risk is a well-known and widely used risk measure by financial institutions. Value at Risk "measures the potential loss in the value of a risky asset or portfolio over a defined period for a given confidence interval". [7] "Perhaps the greatest advantage of Value at Risk (VaR) is that it summarizes in a single, easy to understand number the downside risk of an institution due to financial market variables." [8]

If X represents the return of a portfolio and the returns have distribution F, then given a confidence level (1-τ), $\mathrm{VaR}_\tau(\mathrm{X})$ can be defined as:

(9) $$VaR_\tau(X) = \inf\{x: F(x) \geq \tau\}$$

VaR is essentially the τ-quantile of the return distribution F as defined by equation (1). VaR can also be implicitly defined by:

(10) $$P(X \leq VaR_\tau) = \tau$$

I.e. there is a $(100 \times \tau)\%$ chance of the portfolio return (X) becoming less than VaR_τ over a defined period or in other words, with confidence level (1- τ) the portfolio return will not be less then VaR_τ.

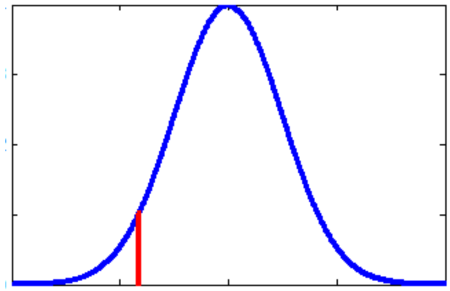


Figure 2

When calculating VaR one needs to choose what method to use. The approach used here involves using historical data of returns to generate an empirical distribution. To then find the $(100 \times \tau)\%$ VaR, one simply takes the τ-quantile of that empirical distribution (F) according to equations (1) and (9). By using this method it is assumed that the empirical distribution from the historical data can be used as a prediction for future returns. Notice that when using this method there is no need for estimating mean and standard deviation. Another basic method to calculate VaR is to fit a normal distribution to the empirical distribution and then use the mean and standard deviation from the fitted distribution to estimate VaR (5% VaR would be the mean minus 1,65 times one standard deviation, $\mu - 1{,}65\sigma$). A variety of modified versions of these two basic methods can be used as well as Monte Carlo simulation, described in more detail by Jorion [8] and Damodaran [7].

Value at Risk is typically used by financial institutions to measure market risk of trading portfolios, indicating how market volatility can lead to a potential loss. Value at Risk has become a standard risk management benchmark when it comes to market risk and is also used by regulatory institutions. For example, the Basel II recommendations (by The Basel Committee on Banking Supervision) for market risk bases the capital requirements for banks on Value at Risk [8]

Although VaR is most known for being used to estimate market risk of trading portfolios it can be used in a more broad or different context, and has for example been used to estimate credit risk. The main advantages of VaR are that it is a simple risk measure, one number that is easy to interpret and it is very popular and hence often convenient for comparison. VaR has also its limitations that one should be aware of to not get a false sense of security when using it. Among those limitations is that while VaR estimates a possible loss for a specific quantile it disregards how large that loss can get below that quantile. Another risk measure called Expected Shortfall (ES) estimates the risk below the VaR limit [9]. However both VaR and ES estimates are based on historical volatility which may not represent the future volatility properly and it may fail to take into account extreme and unusual events that can occur and affect financial stability. Another limitation of VaR is that it is not necessarily additive, i.e. VaR of two portfolios cannot be summed up to get the VaR of the combined portfolio. Correlation between the portfolios needs to be taken into account.

3 The Model

3.1 The Original CoVaR Model

Given the definition of VaR, the CoVaR model can now be explained. CoVaR stands for Conditional Value at Risk. CoVaR of the financial system (or a particular bank, portfolio of asset, etc.) is defined as the VaR of the financial system, conditional on some scenario at a particular bank or a set of banks. [2]

Assume now that X^j represents asset returns of the financial system (or bank j) and X^i represents the asset returns of bank i. While equation (10) describes the definitions of VaR, the following equation has a conditional event added to the definition of VaR. Equation (11) implicitly defines CoVaR of the financial system (or bank j) conditional on bank i being at its q% VaR level. q is a given quantile of the distribution of X^j .

(11) $$P\left(X^j \le CoVaR_q^{j|i} \middle| X^i = VaR_q^i\right) = q$$

One can say that there is a q% chance of the system returns (X^j) becoming less than $CoVaR_q^{j|i}$ within a specified time period given that returns of bank i are at its q% VaR level.

To measure how much bank i contributes to the financial system (or bank j) VaR during stressful times in bank i, Adrian and Brunnermeier [2] look at the difference between the system VaR conditional on bank i being at its VaR level minus the system VaR conditional on bank i being at its median level, i.e.:

(12) $$\Delta CoVaR_q^{j|i} = \begin{pmatrix} CoVaR\ of\ instution\ j\ conditional\ on \\ institution\ i\ being\ at\ its\ VaR\ level \end{pmatrix} - \begin{pmatrix} CoVaR\ of\ instution\ j\ conditional\ on \\ institution\ i\ being\ at\ its\ median\ level \end{pmatrix}$$

(13) $$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i = VaR_q^i} - CoVaR_q^{j|X^i = Median^i}$$

3.1.1 Estimation

Quantile regression is an efficient way to estimate CoVaR relations between the financial system and each bank and between pairs of banks. When calculating VaR and CoVaR, the focus is on the lower quantiles of a distribution and therefore it is convenient to use quantile regression instead of e.g. OLS regression. Time series of asset returns for each bank is used to estimate the distribution of X^i and X^{system}. Adrian and Brunnermeier [2] generate the asset returns of the system by taking the weighted sum of asset returns of each bank in the system weighted by their lagged market valued assets. With those time series one can do the following quantile regression.

(14) $$X^j = \alpha_q^i + \beta_q^i X^i + \varepsilon$$

This equation describes the regression of X^j (where j can be the system or any bank j ≠ i) on X^i for every institution i. The quantile regression coefficient β_q^i estimates the change in a specified quantile q of X^j produced by a one unit change in X^i. I.e.

(15) $$\hat{X}_q^{j,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i$$

By using the definitions (13) and (15) above:

(16) $$CoVaR_q^{j|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i$$

(17) $$CoVaR_q^{j|X^i=VaR_{50}^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_{50}^i$$

And finally, banks i contribution to bank j (or the financial system if j=system) VaR is:

(18) $$\Delta CoVaR_q^{j|i} = \hat{\beta}_q^i (\mathrm{VaR}_q^i - \mathrm{VaR}_{50}^i)$$

3.2 Extensions to the original CoVaR Model

3.2.1 The system

Lopez-Espinosa, Moreno, Rubia and Valderrama [10] propose in a working paper written for the International Monetary Fund ways to utilize and extend the CoVaR model by Adrian and Brunnermeier. One change they suggest is to generate the asset returns of the system by taking the weighted sum of asset returns of each bank in the system weighted by their lagged market valued assets, but unlike in [2] to leave out bank i in the weighted sum when regressing $\mathrm{X}^{\mathrm{system}}$ on that bank i. I.e. generating n number of time series for $\mathrm{X}^{\mathrm{system}}$, n being the number of banks considered. This method is used in this paper. That should prevent unwanted correlation effect when the number of banks n is not large or when a particular bank is a large part of the system.

3.2.2 Asymmetry

In the IMF working paper [10] the authors also suggest taking into account possible asymmetry in how different quantiles of banks asset returns are correlated with asset returns of the system and other banks. To take this asymmetry into account equation (14) is restructured with new indicator variables, $I_{(X^i<0)}$ taking the value one if $X^i < 0$, else zero and $I_{(X^i \geq 0)}$taking the value one if $X^i \geq 0$, else zero.

(19) $$X_q^j = \alpha_q^i + \beta(-)_q^i X^i I_{(X^i<0)} + \beta(+)_q^i X^i I_{(X^i>0)} + \varepsilon$$

3.2.3 Add volatility index, equity index and crisis variable to the analysis

In both [2] and [10] extra economic state variables are added to the regression model in order to obtain an ever better estimate of the relation between individual banks, the financial system and various economic scenarios. In this paper a volatility index (with parameter $\beta(eq)$), an equity index (with parameter $\beta(vol)$) and a crisis variable (with parameter $\beta(crisis)$) are added to the model according to equation (20).

$$X_q^j = \alpha_q^i + \beta(-)_q^i X^i I_{(X^i<0)} + \beta(+)_q^i X^i I_{(X^i>0)} + \beta(vol)_q^i X^{vol} + \beta(eq)_q^i X^{eq} + \beta(crisis)_q^i X^{crisis} + \varepsilon \quad (20)$$

3.3 Different windows - Before and after crisis

The estimation of CoVaR depends on the data chosen for the regression model (14). Using different time frames of the same data can also produce different result. Adams, Füss, Gropp [11] have explored the subject of how CoVaR estimation depends on the historical time frame chosen for the regression model. They analyse if the CoVaR results depend on the state of the economy during the time frame used and hence call their method State Dependent Sensitivity Value-at-Risk (SDSVaR). They conclude that during volatile times there is more spillover risk in the system than during normal or tranquil times. Hence this last part of the analysis covers a comparison of CoVaR results for two different time periods, before and after the 2008 crisis. If the results are in accordance to Adams, Füss, Gropp [11] then they should indicate larger spillover risk in the second time period (after the crisis) since that period is by far more volatile.

4 Data

Adrian and Brunnermeier chose to analyse at VaR and CoVaR of growth rates of market-valued total assets and that is done here. The argument being that the market value of assets is closely related to the supply of credit to the real economy.

The growth rate of market valued total assets X_t^i for bank i at time t is defined by [2]:

$$(21) \qquad X_t^i = \frac{ME_t^i\left(\frac{BA_t^i}{BE_t^i}\right) - ME_{t-1}^i\left(\frac{BA_{t-1}^i}{BE_{t-1}^i}\right)}{ME_{t-1}^i\left(\frac{BA_{t-1}^i}{BE_{t-1}^i}\right)} = \frac{LEV_t^i ME_t^i - LEV_{t-1}^i ME_{t-1}^i}{LEV_{t-1}^i ME_{t-1}^i} == \frac{MA_t^i - MA_{t-1}^i}{MA_{t-1}^i}$$

Where:

BA_t^i = The book value of total assets of institution i at time t.
BE_t^i = The book value of total equity of institution i at time t.
ME_t^i = The market value of total equity of institution i at time t.
$LEV_t^i = BA_t^i/BE_t^i =$ The leverage i.e. total assets / total equity at time t.
MA_t^i = The market valued total financial assets of institution i at time t.

I.e. the Price-to-Book equity value is used to transform book-valued total assets into market-valued total assets. The growth rate of market valued total assets for the banking sector X_t^{system} is simply the average growth rate of market-valued total assets of the financial institutions.

Each time period (time t) – (time t-1) is one week and hence the results for VaR and CoVaR are a prediction for one week ahead in time.

The data used to obtain time series of market valued total assets are daily values of market capitalization (the market value of total equity) and quarterly balance sheet data of book-valued total assets and equity, all available from Bloomberg and other similar data sources. The daily market data is converted to a weekly frequency and matched with interpolated values of the quarterly balance sheet data. With that it is possible to generate weekly time series of growth rates of market-valued total assets according to equation (21). The time series span the time period from April 1999 to year-end 2011 for the four largest Swedish banks. When analysing the Swedish banks with 44 other banks from around the world the time series span April 2000 to year-end 2011. The time period was chosen so, because of data availability and the 44 international banks used are chosen from a list of banks in the IMF working paper [10] where relatively large banks from variety of worldwide countries were used. Figure 2 shows weekly growth rate of market valued total asset for one Swedish bank and figure 3 shows the empirical distribution from that same bank where the red line shows the 5th quantile.

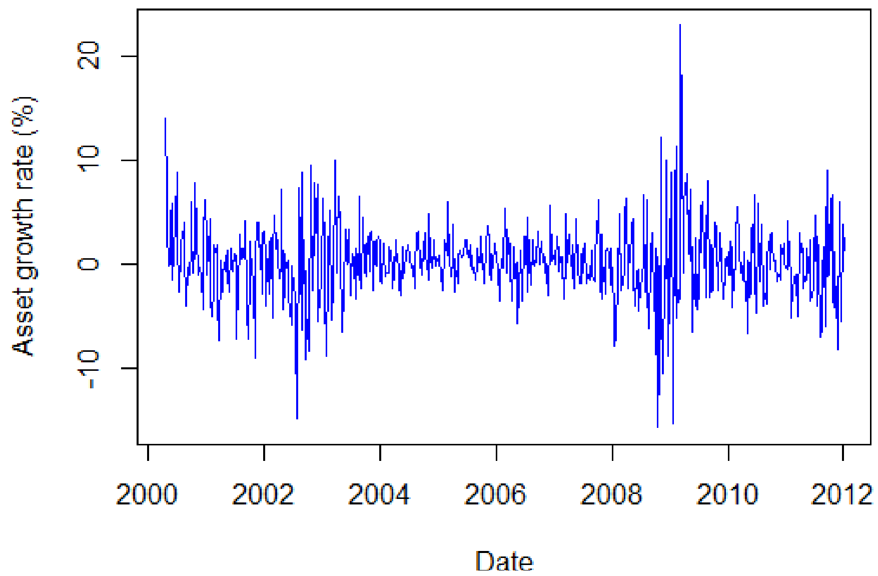


Figure 3

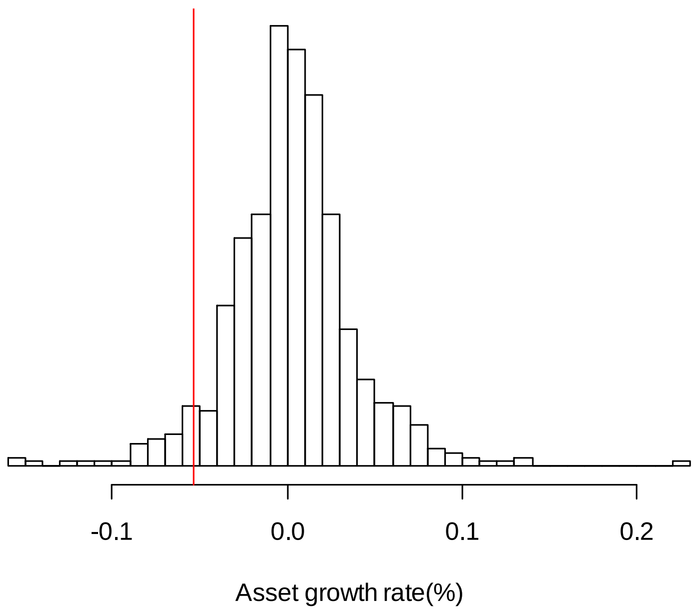


Figure 4

The state variables later added to the model are a volatility index, an equity index and a crisis dummy. The volatility index used is Dow Jones EURO STOXX 50 Volatility Index (V2X in Bloomberg) which is a volatility index based on the EURO STOXX 50 equity index that represents 50 large European stocks. The volatility index is here used to represent volatility in European markets. Daily values of the volatility index are available from Bloomberg and similar data sources. The equity index used is FTSEurofirst 300 Index (E300 in Bloomberg) which covers 300 large European stocks. Daily values are also available from Bloomberg and similar data sources. The growth rate of the equity index is used in the regression models and it is used to represent the growth rate of European equity markets. Finally the last state variable, the crisis dummy takes a value of 1 if it is both after year-end 2007 and the asset growth rate of the bank/system being regressed on is negative. These three daily time series are collapsed to a weekly frequency and matched to the time span of the previously described data.

5 Results

5.1 The Swedish Banking System

5.1.1 The original CoVaR model

Following are results for VaR and ΔCoVaR of growth rates of market valued total assets. When analysing the Swedish banking system in its isolation, the four largest Swedish banks SEB, Handelsbanken (SHB), Nordea (NDA) and Swedbank (SWED) are considered as they account for approximately 75% of the system. First it is relevant to look at the unconditional VaR for the individual institutions based on the empirical distributions of weekly growth rates. In table 1 are estimates for 5% VaR and the median growth rate (50% VaR).

Table 1 – VaR of individual banks

	NDA SS	SEBA SS	SHBA SS	SWEDA SS
5% VaR	-5.29%	-6.23%	-4.69%	-6.52%
50% VaR	0.19%	0.15%	0.08%	0.19%

As explained before, quantile regression is used to estimate how each bank is related to specific quantiles of the system growth rate and from those results it is possible to estimate CoVaR and ΔCoVaR. Figures 3 and 4 describe how the regression coefficients change with quantiles when regressing the system on each of the banks. The blue lines represent the alpha (figure 3) and beta (figure 4) coefficients and the grey lines above and below represent 90% confidence intervals. For comparison the regression coefficient from OLS regression is shown with red lines.

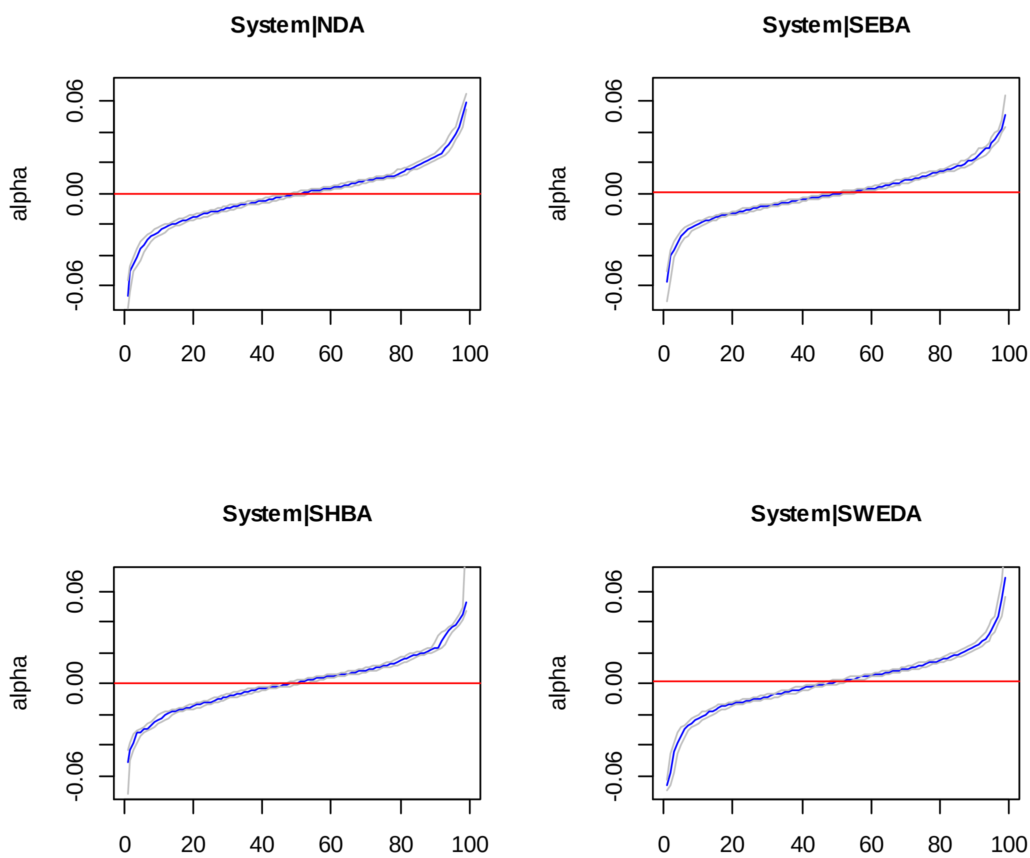


Figure 5 – The quantile regression parameter α as a function of the regression quantile q

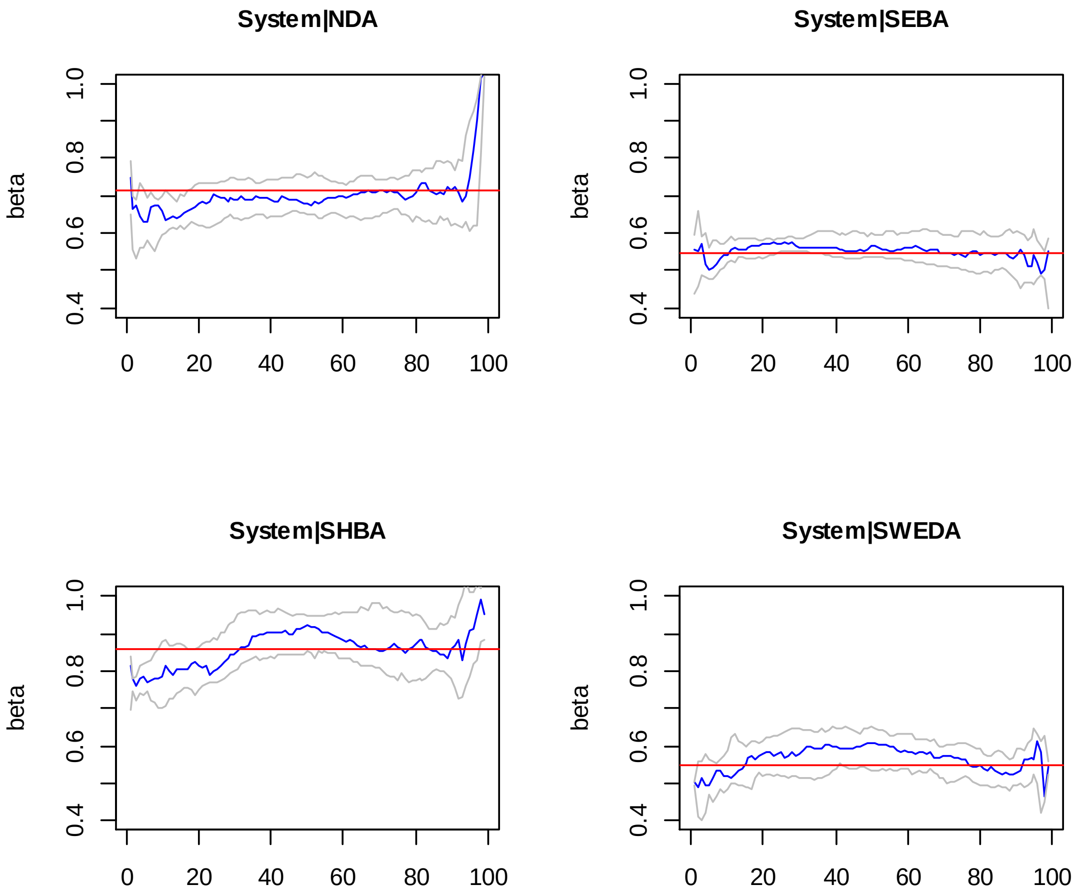


Figure 6 - The quantile regression parameter β as a function of the regression quantile q

Parameter estimates and confidence intervals for the 5th quantile when the system is regressed on each bank i, are listed in table 2. The derivation of confidence intervals is explained in the Appendix (A1).

Table 2 – The quantile regression parameters when regressing the system on bank i

		$X^{SYSTEM} \mid X^{bank\ i}$		
		value	(conf.int)	
NDA SS	α	-0.036	-0.044	-0.032
	β (X^i)	0.629	0.559	0.719
SEBA SS	α	-0.028	-0.033	-0.025
	β (X^i)	0.500	0.479	0.563
SHBA SS	α	-0.031	-0.034	-0.030
	β (X^i)	0.787	0.736	0.819
SWEDA SS	α	-0.034	-0.040	-0.028
	β (X^i)	0.495	0.469	0.563

From these estimates and by using equation (16), CoVaR and ΔCoVaR for the system conditional on each bank are calculated and presented in table 3. $\mathrm{CoVaR}^{\mathrm{system|bank\ i}}$ is an estimation of the system VaR conditional on bank i being at its 5% VaR level. E.g. $\mathrm{CoVaR}^{\mathrm{system|SEB}}$ = -5,90% indicates that the system 5% VaR is -5,90% when SEB is at its 5% VaR level. The main focus is on the ΔCoVaR results. ΔCoVaR for the system conditional on each bank is also presented in table 2. $\Delta\mathrm{CoVaR}^{\mathrm{system|bank\ i}}$

indicates how much bank i adds to the system VaR when that bank i moves from its median state to its 5% VaR level. As an example $\Delta \mathrm{CoVaR}^{\mathrm{system|SEB}}$ = -3,19% indicates that SEB adds 3,19% to the system 5% VaR when SEB moves from its median state to its 5% VaR level.

Table 3 – CoVaR and ΔCoVaR of the system conditional on bank i

	5% $\mathrm{CoVaR}^{\mathrm{system\,|\,bank\,i}}$	5% $\Delta\mathrm{CoVaR}^{\mathrm{system\,|\,bank\,i}}$
NDA SS	-6.90%	-3.45%
SEBA SS	-5.90%	-3.19%
SHBA SS	-6.81%	-3.75%
SWEDA SS	-6.63%	-3.33%

It is possible to estimate the relationship between individual banks as well, i.e. estimate how each bank affects specific quantiles of another bank. The results below are from the 5th quantile regression of each bank j on each bank i. Plots of the parameters as a function of quantiles can be found in the Appendix (A3).

Table 4 - The quantile regression parameters when regressing each bank j on each bank i

		$X^{NDA}\,|\,X^{i}$			$X^{SEBA}\,|\,X^{i}$			$X^{SHBA}\,|\,X^{i}$			$X^{SWEDA}\,|\,X^{i}$		
X^{i}		value	(conf.int)		value	(conf.int)		value	(conf.int)		value	(conf.int)	
NDA SS	α				-0.0490	-0.0553	-0.0449	-0.0373	-0.0418	-0.0328	-0.0521	-0.0630	-0.0496
	β (X^{i})				0.7176	0.6166	0.8262	0.4807	0.4466	0.5357	0.7939	0.7563	0.8531
SEBA SS	α	-0.0380	-0.0426	-0.0365				-0.0338	-0.0383	-0.0309	-0.0444	-0.0502	-0.0404
	β (X^{i})	0.5131	0.4967	0.5281				0.4216	0.3472	0.4985	0.6871	0.6223	0.7314
SHBA SS	α	-0.0379	-0.0424	-0.0360	-0.0434	-0.0512	-0.0402				-0.0529	-0.0596	-0.0471
	β (X^{i})	0.7138	0.6328	0.7280	1.0174	0.9057	1.1640				0.8526	0.8061	0.9855
SWEDA SS	α	-0.0438	-0.0525	-0.0377	-0.0417	-0.0490	-0.0376	-0.0364	-0.0418	-0.0321			
	β (X^{i})	0.5162	0.4437	0.5573	0.7645	0.6710	0.8207	0.4063	0.3367	0.4550			

$\mathrm{CoVaR}^{\mathrm{bank\,j|bank\,i}}$ and $\Delta\mathrm{CoVaR}^{\mathrm{bank\,j|bank\,i}}$ are calculated from these parameters and the results are presented in table 5. Similar to before $\mathrm{CoVaR}^{\mathrm{bank\,j|bank\,i}}$ indicates the VaR of bank j conditional on bank i being at its VaR level and $\Delta\mathrm{CoVaR}^{\mathrm{bank\,j|bank\,i}}$ is an estimation of how much bank i adds to VaR of bank j when bank i moves from its median state to its 5% VaR level. As an example Nordea (NDA) adds -2,64% to 5% VaR of Handelsbanken (SHBA) when Nordea moves from its median state to its VaR level. Handelsbanken however adds -3,27% to 5% VaR of Nordea when Handelsbanken moves to its 5% VaR level.

Table 5 – CoVaR and ΔCoVaR of bank j conditional on bank i

		5% $CoVaR^{bank\ j\|bank\ i}$		
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-8.70%	-6.28%	-9.41%
SEBA SS	-7.00%		-6.00%	-8.72%
SHBA SS	-7.14%	-9.11%		-9.29%
SWEDA SS	-7.74%	-9.15%	-6.29%	
		5% $\Delta CoVaR^{bank\ j\|bank\ i}$		
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-3.93%	-2.64%	-4.35%
SEBA SS	-3.27%		-2.69%	-4.39%
SHBA SS	-3.40%	-4.85%		-4.06%
SWEDA SS	-3.46%	-5.13%	-2.73%	

Finally are results that describe how the system affects each bank. $\mathrm{CoVaR}^{\mathrm{bank\ i|system}}$ and $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i|system}}$ are listed in table 7 for the 5th quantile (plots of the parameters are in the Appendix (A4)). $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i|system}}$ indicates each banks exposure risk, i.e. how sensitive a bank is to the financial system going into distress. For example the system adds -5,26% to Swedbanks 5% VaR when the system moves from its median state to its 5% VaR level. When investigating table 7 it is possible to draw the conclusion that Nordea and Handelsbanken are less exposed to systemic risk since their $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i|system}}$ values are significantly lower than for SEB and Swedbank.

Table 6 – The quantile regression parameters when regressing the bank i on the system

		$X^{bank\ i} \| X^{SYSTEM}$		
		value	(conf.int)	
NDA SS	α	-0.038	-0.040	-0.035
	β (X^{system})	0.753	0.735	0.776
SEBA SS	α	-0.045	-0.050	-0.040
	β (X^{system})	1.196	0.964	1.292
SHBA SS	α	-0.030	-0.036	-0.026
	β (X^{system})	0.624	0.562	0.710
SWEDA SS	α	-0.044	-0.051	-0.039
	β (X^{system})	0.993	0.978	1.148

Table 7– CoVaR and ΔCoVaR of bank j conditional on the system

	5% $CoVaR^{bank\ i\|system}$	5% $\Delta CoVaR^{bank\ i\|system}$
NDA SS	-7.62%	-3.96%
SEBA SS	-10.23%	-5.98%
SHBA SS	-6.23%	-3.42%
SWEDA SS	-9.43%	-5.26%

The figures below show a summary of the 5% ΔCoVaR relationships consistent with tables 3, 5 and 7.

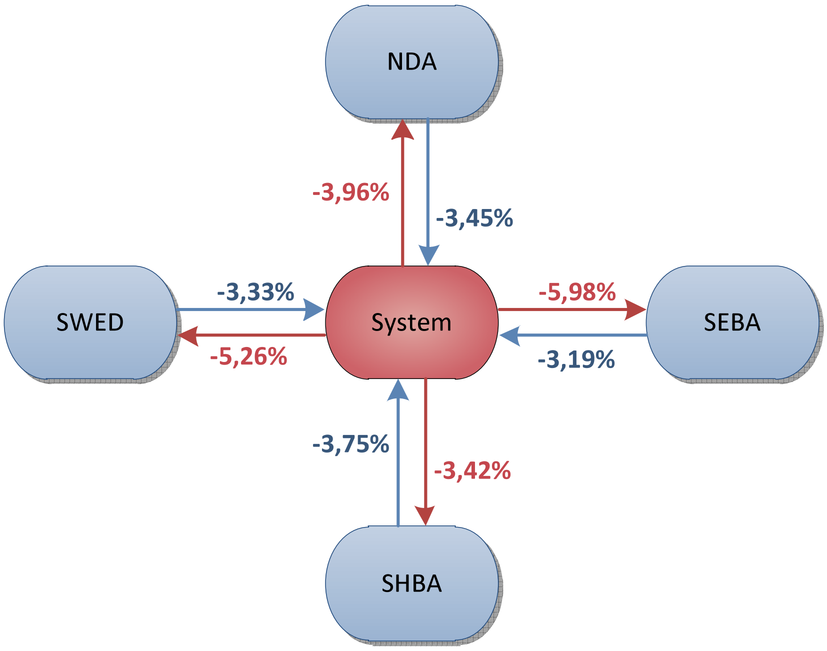


Figure 7- ΔCoVaR relationships between the system and each bank

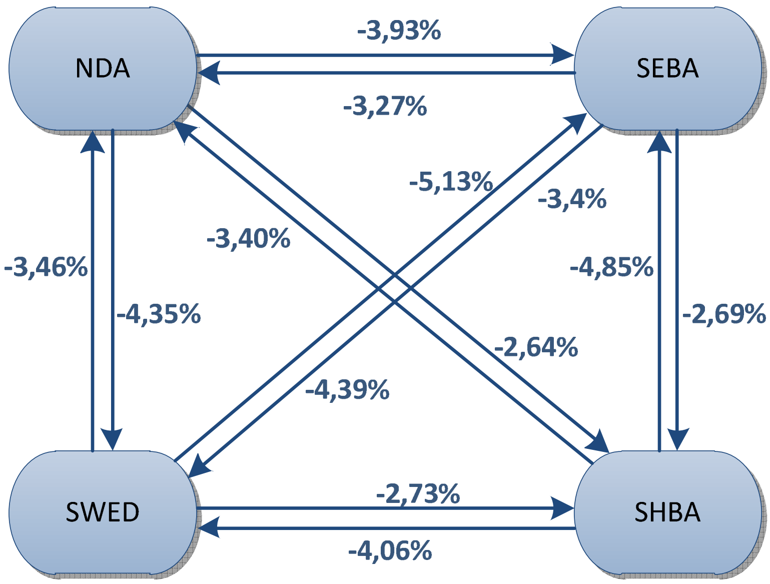


Figure 8 - ΔCoVaR relationships between the banks

5.1.2 The Asymmetric CoVaR model

There are many options available when it comes to extending the original model depending on the goal and intentions each time. It might be of interest to assume that the asset growth of "bank i" is negative $(X^{bank\ i} < 0)$ when estimating how much that bank can contribute to systemic risk when going into distress. That can be done with asymmetric quantile regression as described with equation (19) and again here.

$$X_q^{system} = \alpha_5^i + \beta(-)_5^i X^i I_{(X^i<0)} + \beta(+)_5^i X^i I_{(X^i>0)} + \varepsilon$$

The asymmetric quantile regression results are in table 8. Comparison with the results from the original model in table 2 indicates much stronger relationship between the 5th quantile of the system growth rate and the negative part of banks i growth rate then when assuming symmetric relationship. It is also interesting to compare the plots of the parameters as a function of quantiles between the original (figures 5 and 6) and the asymmetric model (figures 8, 9 and 10).

Table 8 - The quantile regression parameters when regressing the system on bank i

		$X^{SYSTEM} \mid X^i$		
		value	(conf.int)	
NDA SS	α	-0.025	-0.029	-0.019
	β (X^i<0)	1.083	0.924	1.703
	β (X^i>0)	0.321	0.070	0.408
SEBA SS	α	-0.018	-0.024	-0.014
	β (X^i<0)	0.834	0.650	1.152
	β (X^i>0)	0.258	0.008	0.384
SHBA SS	α	-0.021	-0.024	-0.015
	β (X^i<0)	1.248	0.976	1.515
	β (X^i>0)	0.371	-0.049	0.526
SWEDA SS	α	-0.019	-0.024	-0.016
	β (X^i<0)	0.963	0.827	1.279
	β (X^i>0)	0.021	-0.020	0.238

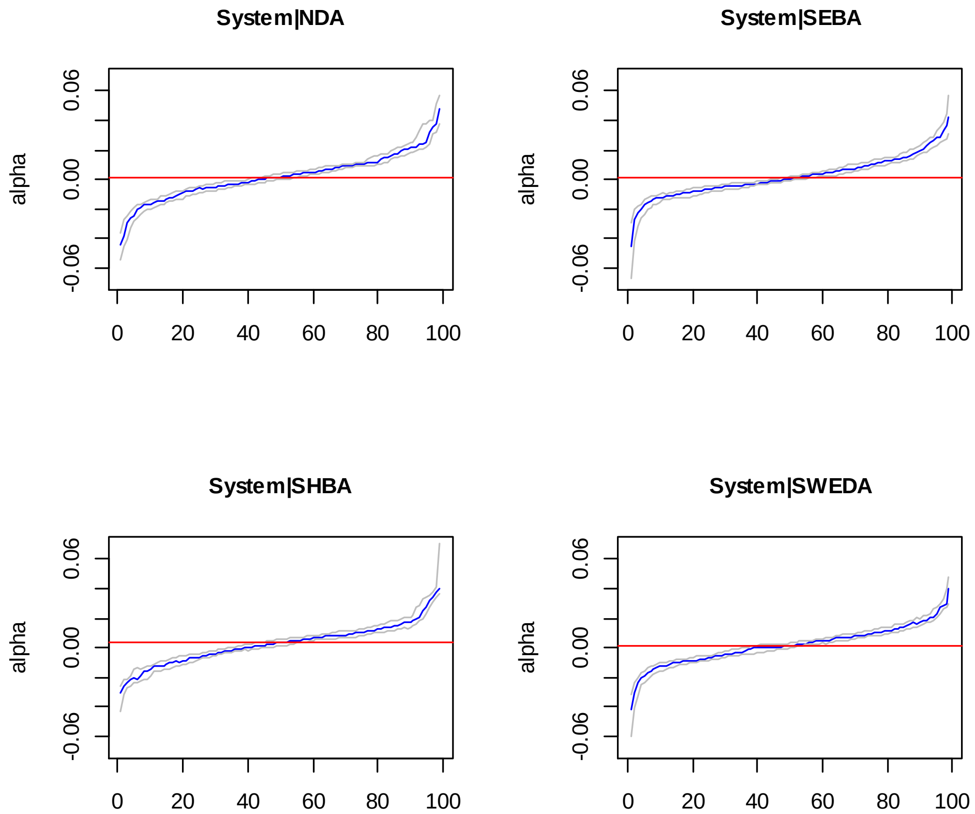


Figure 9 - The quantile regression parameter α as a function of the regression quantile q

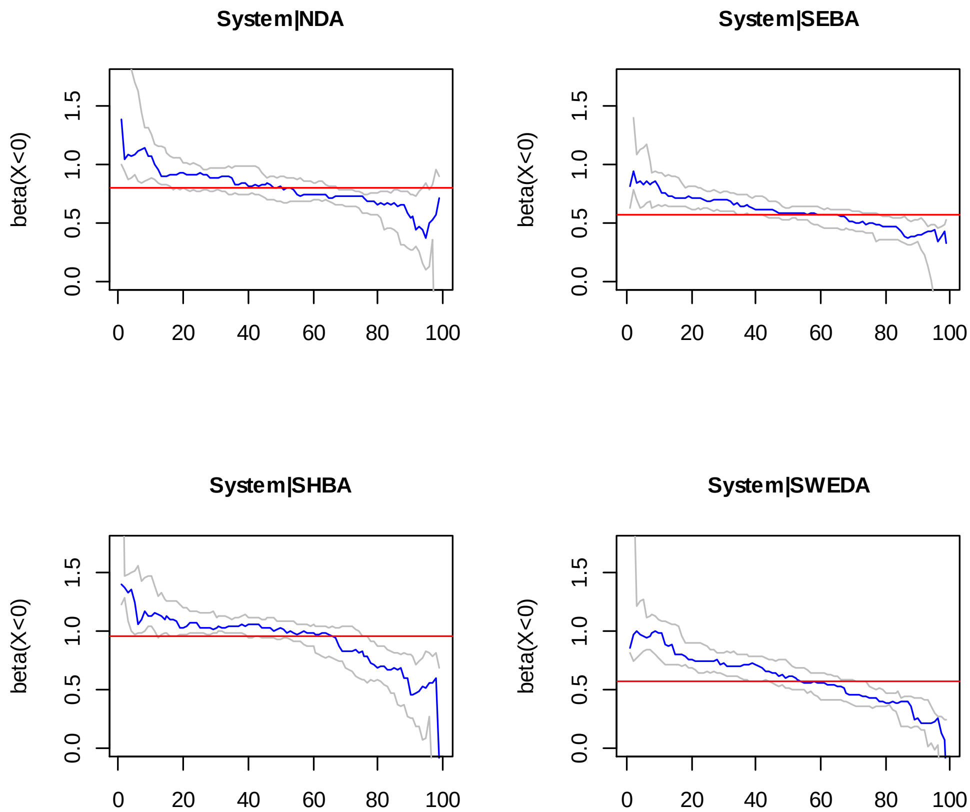


Figure 10 - The quantile regression parameter β(-) as a function of the regression quantile q

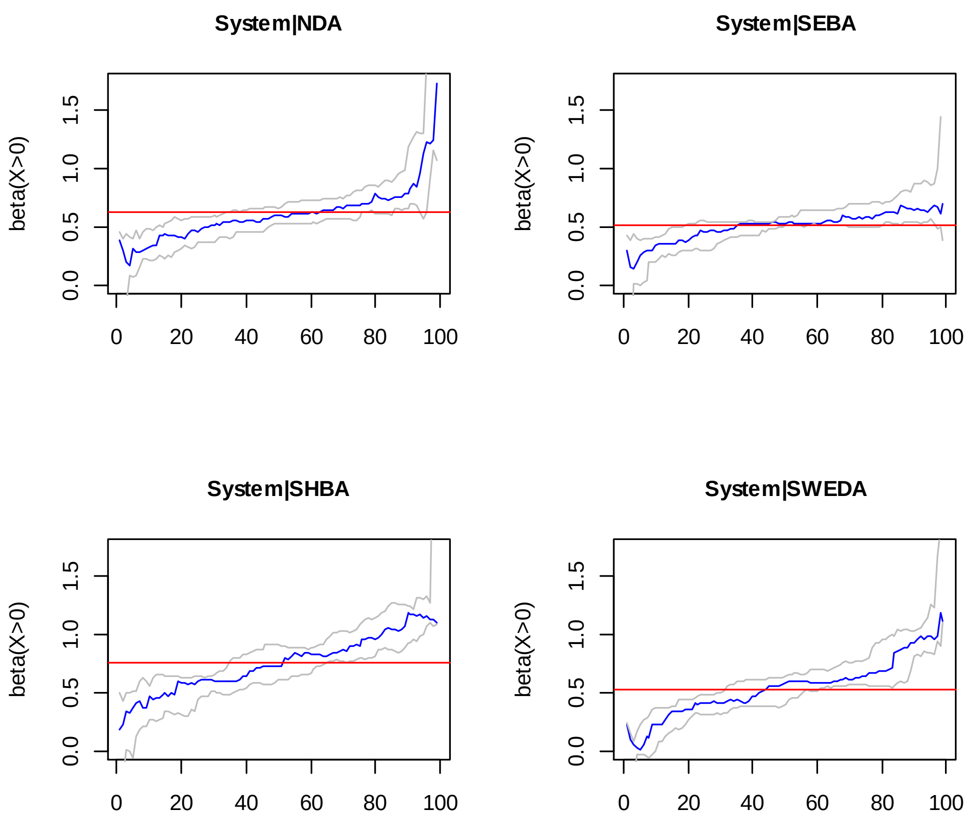


Figure 11 - The quantile regression parameter β(+) as a function of the regression quantile q

To estimate CoVaR and ΔCoVaR when assuming asymmetry and being cautious of not underestimating possible contagion from the banks to the system , the first two parameters from the regression are used according to the following equation ($\beta(-)_5^i$ being the parameter for the negative asset growth rate)

(22) $$CoVaR_5^{system|X^i=VaR_5^i} = \hat{\alpha}_5^i + \beta(-)_5^i VaR_5^i,$$

and as before (equation (18)) gives

$$\Delta CoVaR_5^{system|i} = \beta(-)_5^i (VaR_5^i - VaR_{50}^i).$$

Table 9 - CoVaR and ΔCoVaR of the system conditional on bank i

Asymmetric	5% CoVaR$^{system\|bank\ i}$	5% ΔCoVaR$^{system\|bank\ i}$	Original	5% CoVaR$^{system\|bank\ i}$	5% ΔCoVaR$^{system\|bank\ i}$
NDA SS	-8.23%	-5.94%	NDA SS	-6.90%	-3.45%
SEBA SS	-6.96%	-5.32%	SEBA SS	-5.90%	-3.19%
SHBA SS	-7.93%	-5.95%	SHBA SS	-6.81%	-3.75%
SWEDA SS	-8.20%	-6.46%	SWEDA SS	-6.63%	-3.33%

Comparing the asymmetric results with the previous results from the original model, the contribution by each bank to systemic risk is larger with this method. Also interesting is that the asymmetric results differ more between banks. E.g. while according to the original model the four banks contribute similarly much to systemic risk when going into distress, then according to the asymmetric model, Swedbank contributes more than 1% more to system risk than SEB when going into distress.

CoVaR and ΔCoVaR for each bank j conditional on each bank i is estimated by the same method:

Table 10 - CoVaR and ΔCoVaR of bank j conditional on bank i

Asymmetric					Original				
	5% $CoVaR^{bank\ j\|bank\ i}$					5% $CoVaR^{bank\ j\|bank\ i}$			
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS	*bank i\bank j*	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-10.73%	-7.21%	-10.93%	NDA SS		-8.70%	-6.28%	-9.41%
SEBA SS	-8.71%		-6.65%	-10.32%	SEBA SS	-7.00%		-6.00%	-8.72%
SHBA SS	-8.16%	-10.78%		-10.68%	SHBA SS	-7.14%	-9.11%		-9.29%
SWEDA SS	-9.87%	-10.14%	-7.76%		SWEDA SS	-7.74%	-9.15%	-6.29%	
	5% $\Delta CoVaR^{bank\ j\|bank\ i}$					5% $\Delta CoVaR^{bank\ j\|bank\ i}$			
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS	*bank i\bank j*	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-7.58%	-4.96%	-7.60%	NDA SS		-3.93%	-2.64%	-4.35%
SEBA SS	-6.28%		-4.23%	-7.21%	SEBA SS	-3.27%		-2.69%	-4.39%
SHBA SS	-5.89%	-8.18%		-4.96%	SHBA SS	-3.40%	-4.85%		-4.06%
SWEDA SS	-7.87%	-7.35%	-5.75%		SWEDA SS	-3.46%	-5.13%	-2.73%	

As when analysing CoVaR of the system there is more variety in the results from the asymmetric model than the original model. Few other interesting conclusions can be drawn from table 10. E.g. SEB and Swedbank can be considered as more volatile or risky banks since they are more sensitive to other banks going into distress. With the same argument, Handelsbanken could be considered as the most stable and resilient bank when other banks go into distress.

Finally are the CoVaR exposure results. These results strengthen the conclusion mentioned above that SEB and Swedbank are more volatile or risky banks since they are by far more sensitive than Nordea and Handelsbanken to the system going into distress. E.g. the system contributes -4,31% to 5% VaR of Handelsbanken compared to -8,82% to 5% VaR of Swedbank when the system goes into distress.

Table 11 - CoVaR and ΔCoVaR of bank j conditional on the system

Asymmetric	5% $CoVaR^{bank\ i\|system}$	5% $\Delta CoVaR^{bank\ i\|system}$	Original	5% $CoVaR^{bank\ i\|system}$	5% $\Delta CoVaR^{bank\ i\|system}$
NDA SS	-8.74%	-6.02%	NDA SS	-7.62%	-3.96%
SEBA SS	-10.54%	-7.70%	SEBA SS	-10.23%	-5.98%
SHBA SS	-6.50%	-4.31%	SHBA SS	-6.23%	-3.42%
SWEDA SS	-11.68%	-8.82%	SWEDA SS	-9.43%	-5.26%

5.1.3 Volatility index, equity index and crisis variable

As described in chapter 3.2.3 it can be interesting to add economic state variables to the regression model since it can help predict how systemic risk is related to various scenarios in the economy. See equation (20).

Table 12 - CoVaR of the system conditional on bank i

		$X^{SYSTEM} \mid X^{bank\ i}$					
		value	(conf.int)			β_k*X	5% $CoVaR^{system \mid bank\ i}$
NDA SS	α	-0.0046	-0.0109	-0.0012	α	-0.46%	
	β (X^i<0)	0.9688	0.7559	1.1911	β (X^i<0) * X_5^i	-5.13%	
	β (X^i>0)	0.4934	0.3580	0.5626			
	β (vol)	-0.00083	-0.00107	-0.00065	β (vol) * X_{75}^{vol}	-2.45%	
	β (eq)	0.0275	-0.0851	0.1207	β (eq) * X_{25}^{eq}	-0.04%	
	β (crisis)	0.0004	-0.0372	0.0129	β (crisis)*1	0.04%	-8.04%
SEBA SS	α	0.0052	-0.0005	0.0101	α	0.52%	
	β (X^i<0)	0.6947	0.5447	0.8437	β (X^i<0) * X_5^i	-4.33%	
	β (X^i>0)	0.3655	0.1665	0.4959			
	β (vol)	-0.00110	-0.00146	-0.00083	β (vol) * X_{75}^{vol}	-3.25%	
	β (eq)	0.0532	-0.0456	0.1438	β (eq) * X_{25}^{eq}	-0.07%	
	β (crisis)	-0.0005	-0.0064	0.0084	β (crisis)*1	-0.05%	-7.18%
SHBA SS	α	-0.0058	-0.0190	-0.0002	α	-0.58%	
	β (X^i<0)	1.0555	0.8670	1.3515	β (X^i<0) * X_5^i	-4.95%	
	β (X^i>0)	0.3923	0.1657	0.6084			
	β (vol)	-0.00065	-0.00102	-0.00018	β (vol) * X_{75}^{vol}	-1.90%	
	β (eq)	0.0446	0.0004	0.2757	β (eq) * X_{25}^{eq}	-0.06%	
	β (crisis)	-0.0008	-0.0300	0.0052	β (crisis)*1	-0.08%	-7.57%
SWEDA SS	α	-0.0087	-0.0137	-0.0038	α	-0.87%	
	β (X^i<0)	0.8694	0.6858	0.9716	β (X^i<0) * X_5^i	-5.67%	
	β (X^i>0)	0.0166	-0.0193	0.2416			
	β (vol)	-0.00039	-0.00063	-0.00023	β (vol) * X_{75}^{vol}	-1.13%	
	β (eq)	0.0726	0.0235	0.1095	β (eq) * X_{25}^{eq}	-0.10%	
	β (crisis)	-0.0062	-0.0341	-0.0017	β (crisis)*1	-0.62%	-8.39%

The regression parameters (to the left in table 12) indicate the relationship between the 5th quantile of the system asset growth rate to each of the variables. The right side of the table shows an example of how one can calculate 5% $\mathrm{CoVaR}^{\mathrm{system|bank\ i}}$. In this example it is assumed that the asset growth rate of bank i is negative i.e. ($X^i < 0$), that equity markets are volatile (by using the 75th quantile of the volatility index, X_{75}^{vol}) and moving downward (by using the 25th quantile of the equity index, X_{25}^{eq}). Each regression coefficient is multiplied with specific quantile of the empirical distribution of corresponding variable.

It is apparent that the variables which have the largest contribution to $\mathrm{CoVaR}^{\mathrm{system|bank\ i}}$ are the variables representing the growth rate of bank i and the market volatility. The equity index variable and the crisis variable have relatively wide confidence intervals and are insignificant.

5.1.4 A final model

Finally, given the previous results, the following regression model could be considered a good method to estimate CoVaR and ΔCoVaR.

(23) $$X_q^{system} = \alpha_q^i + \beta(-)_q^i X^i I_{(X^i<0)} + \beta(+)_q^i X^i I_{(X^i>0)} + \beta(vol)_q^i X^{vol} + \varepsilon$$

Table 13 – CoVaR of the system conditional on bank i

		$X^{SYSTEM} \mid X^i$					
		value	(conf.int)			β_k*X	5% $CoVaR^{system\mid bank\ i}$
NDA SS	α	-0.0052	-0.0097	-0.0009	α	-0.52%	
	β (X^i<0)	0.9609	0.8111	1.1790	β (X^i<0) * X_5^i	-5.09%	
	β (X^i>0)	0.4789	0.3915	0.5409			
	β (vol)	-0.00080	-0.00105	-0.00067	β (vol) * X_{75}^{vol}	-2.35%	-7.96%
SEBA SS	α	0.0048	-0.0015	0.0099	α	0.48%	
	β (X^i<0)	0.7152	0.5688	0.8217	β (X^i<0) * X_5^i	-4.46%	
	β (X^i>0)	0.3583	0.2005	0.4704			
	β (vol)	-0.00107	-0.00135	-0.00075	β (vol) * X_{75}^{vol}	-3.15%	-7.13%
SHBA SS	α	-0.0049	-0.0185	0.0026	α	-0.49%	
	β (X^i<0)	1.1305	0.9072	1.4035	β (X^i<0) * X_5^i	-5.30%	
	β (X^i>0)	0.4032	0.1154	0.5704			
	β (vol)	-0.00065	-0.00094	-0.00021	β (vol) * X_{75}^{vol}	-1.91%	-7.70%
SWEDA SS	α	-0.0105	-0.0155	0.0012	α	-1.05%	
	β (X^i<0)	0.9043	0.7395	1.0958	β (X^i<0) * X_5^i	-5.89%	
	β (X^i>0)	0.0373	-0.0225	0.2266			
	β (vol)	-0.00034	-0.00105	-0.00018	β (vol) * X_{75}^{vol}	-0.99%	-7.93%

As in the last section, table 13 shows the regression parameters and an example of how 5% $\text{CoVaR}^{\text{system|bank i}}$ can be estimated. Here it also assumed that the asset growth rate of bank i is negative i.e. ($X^i < 0$) and that equity markets are volatile (by using the 75th quantile of the volatility index, X_{75}^{vol}).

5.1.5. Different windows - Before and after crisis

As explained in section 3.3, CoVaR estimation depends on the historical data time frame used for the regression. Following is a comparison of CoVaR results using two different historical data time frames. The first one is from April 1999 to year-end 2007 and the second one is from year-end 2007 to year-end 2011, the second period being more stressful and volatile because of the 2008 financial crisis. In the previous sections, VaR and CoVaR were calculated on a weekly basis but here it is done on a daily basis. That is done in order to have enough data points for each time period. Table 14 presents an analysis of the system CoVaR conditional on each bank i for both time periods. In all cases except for Swedbank, the parameters suggest a stronger relationship between the system and each bank in the second more volatile period. Then after using equations (16) and (18) to calculate CoVaR and ΔCoVaR the difference is quite large.

Table 14 - Comparison of CoVaR and ΔCoVaR of the system conditional on bank i , from different data

Before 1.1.2008

	α	(conf.int)		β (X^i)	(conf.int)		5% $CoVaR^{System\|bank\ i}$	5% $\Delta CoVaR^{System\|bank\ i}$
NDA SS	-0.018	-0.020	-0.017	0.521	0.482	0.560	-3.34%	-1.50%
SEBA SS	-0.018	-0.019	-0.017	0.529	0.478	0.580	-3.48%	-1.65%
SHBA SS	-0.019	-0.021	-0.018	0.655	0.605	0.684	-3.52%	-1.57%
SWEDA SS	-0.018	-0.019	-0.017	0.608	0.560	0.685	-3.53%	-1.70%

From 1.1.2008

	α	(conf.int)		β (X^i)	(conf.int)		5% $CoVaR^{System\|bank\ i}$	5% $\Delta CoVaR^{System\|bank\ i}$
NDA SS	-0.025	-0.029	-0.023	0.827	0.758	0.866	-6.05%	-3.47%
SEBA SS	-0.024	-0.026	-0.022	0.521	0.480	0.535	-5.20%	-2.79%
SHBA SS	-0.026	-0.029	-0.022	0.946	0.896	1.028	-6.38%	-3.75%
SWEDA SS	-0.027	-0.028	-0.024	0.510	0.473	0.552	-5.64%	-3.00%

In table 15 is a similar analysis of the CoVaR of each bank j conditional on each bank i. As in table 14 the regression parameters suggest in general a stronger relationship between the banks in the second period and a hence larger spillover risk, represented by 5% ΔCoVaR. Then finally in table 16 is an analysis of the CoVaR of each bank i conditional on the system. Again the relationships are in most cases stronger in the second period. These results are in accordance with Adams, Füss, Gropp [11], i.e. larger spillover risk in the more volatile period.

Table 15 - Comparison of CoVaR and ΔCoVaR of bank j conditional on bank i, from different data

Before 1.1.2008

	α				β (X^i)			
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-0.025	-0.020	-0.024		0.596	0.456	0.425
SEBA SS	-0.025		-0.021	-0.021	0.601		0.466	0.511
SHBA SS	-0.024	-0.026		-0.022	0.700	0.665		0.562
SWEDA SS	-0.026	-0.024	-0.020		0.635	0.654	0.529	

	5% $CoVaR^{bank\ j\mid bank\ i}$				5% $\Delta CoVaR^{bank\ j\mid bank\ i}$			
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-4.21%	-3.35%	-3.58%		-1.72%	-1.31%	-1.23%
SEBA SS	-4.36%		-3.53%	-3.71%	-1.88%		-1.46%	-1.60%
SHBA SS	-4.13%	-4.17%		-3.58%	-1.68%	-1.59%		-1.35%
SWEDA SS	-4.39%	-4.29%	-3.50%		-1.77%	-1.83%	-1.48%	

After 1.1.2008

	α				β (X^i)			
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-0.036	-0.024	-0.041		1.083	0.687	0.848
SEBA SS	-0.029		-0.026	-0.034	0.506		0.509	0.757
SHBA SS	-0.027	-0.037		-0.042	0.785	1.102		0.836
SWEDA SS	-0.031	-0.032	-0.030		0.454	0.756	0.387	

	5% $CoVaR^{bank\ j\mid bank\ i}$				5% $\Delta CoVaR^{bank\ j\mid bank\ i}$			
bank i\bank j	NDA SS	SEBA SS	SHBA SS	SWEDA SS	NDA SS	SEBA SS	SHBA SS	SWEDA SS
NDA SS		-8.18%	-5.27%	-7.67%		-4.55%	-2.88%	-3.56%
SEBA SS	-5.66%		-5.35%	-7.50%	-2.71%		-2.73%	-4.06%
SHBA SS	-5.82%	-8.12%		-7.52%	-3.11%	-4.36%		-3.31%
SWEDA SS	-5.74%	-7.59%	-5.27%		-2.67%	-4.45%	-2.28%	

Table 16 - Comparison of CoVaR and ΔCoVaR of bank i conditional on the system, from different data

Before 1.1.2008

	α	(conf.int)		β (X^{System})	(conf.int)		5% $CoVaR^{bank\ i\mid System}$	5% $\Delta CoVaR^{bank\ i\mid System}$
NDA SS	-0.023	-0.025	-0.021	0.889	0.780	0.951	-4.4%	-2.1%
SEBA SS	-0.022	-0.023	-0.021	0.860	0.816	0.931	-4.1%	-2.0%
SHBA SS	-0.019	-0.020	-0.018	0.626	0.590	0.663	-3.4%	-1.6%
SWEDA SS	-0.021	-0.022	-0.019	0.625	0.603	0.699	-3.5%	-1.5%

From 1.1.2008

	α	(conf.int)		β (X^{System})	(conf.int)		5% $CoVaR^{bank\ i\mid System}$	5% $\Delta CoVaR^{bank\ i\mid System}$
NDA SS	-0.024	-0.026	-0.022	0.734	0.671	0.789	-5.6%	-3.1%
SEBA SS	-0.032	-0.036	-0.028	1.206	1.147	1.267	-8.2%	-4.9%
SHBA SS	-0.022	-0.027	-0.019	0.763	0.635	0.831	-5.5%	-3.2%
SWEDA SS	-0.034	-0.040	-0.031	0.923	0.861	1.029	-7.1%	-3.7%

The comparison of CoVaR results for different time frames is only done for the simple CoVaR model here, but when done for the more complex regression models explained in sections 5.1.2 and 5.1.3 it in general also shows stronger relationships between the banks and hence larger spillover risk during the second period.

5.2 International banks

The Swedish banking system does not function in its isolation, but is interconnected with the rest of the world. Hence it can give valuable information if it is possible to estimate the extent of how the worldwide interconnection between banks can cause risk to spread through the international financial system.

The Swedish banking system is of main interest in this paper, both in its isolation and also as a part of the worldwide financial system. The Swedish banks are influenced by various events in foreign markets. E.g. a distress in a particular bank in USA or a distress in the German banking system can cause risk contagion to the Swedish banks. In order to investigate this, 44 banks from around the world (see data discussion in chapter 4) have been added to regression analysis.

5.2.1 The simple CoVaR model

As in section 5.1.1, let first use the simple CoVaR model and investigate the following relationship:

$$X_5^{SWE} = \alpha_5^i + \beta_5^i X^i + \varepsilon$$

Here X^{SWE} represents the asset growth rate of the Swedish banking system. X^{SWE} is calculated at each time t by taking the weighted sum of asset growth rate of the banks weighted with the market valued assets of each bank. The goal is then to regress X^{SWE} on each foreign bank i (X^i) and estimate how much each bank may contribute to the risk of the Swedish banking system.

The results are presented in table 17, the regression parameters with their confidence intverval and then corresponding $\mathrm{CoVaR}^{\mathrm{SWE|bank\,i}}$ and $\Delta\mathrm{CoVaR}^{\mathrm{SWE|bank\,i}}$. The banks who according to this, contribute most to the Swedish system 5% VaR when going into distress (5% $\Delta\mathrm{CoVaR}^{\mathrm{SWE|bank\,i}}$) are ING Groep NV (INGA NA), Societe Generale SA (GLE FP), BNP Paribas SA (BNP FP) and UniCredit SpA (UCG IM) all contributing 3,7-3,9%. ING is an international bank from Netherland, the next two are French international banks and UniCredit is an international Italian bank. Both ING and Societe have a rather high individual VaR while BNPs VaR is just a bit above the average. Below is a plot of $\Delta\mathrm{CoVaR}^{\mathrm{SWE|bank\,i}}$ as a function of each banks i individual VaR. After that is a graph of $\Delta\mathrm{CoVaR}^{\mathrm{SWE|bank\,i}}$ as a function of each banks assets. This first plot shows that a large VaR value does not have to indicate large risk spreading to other banks. The other plot shows that it is not save to assume that larger banks (by assets size) contribute more to the risk of other banks when going into distress.

Table 17 - CoVaR and ΔCoVaR of the Swedish banking system conditional on non-Swedish bank i

SWE|bank i	α	(conf.int)		β (X^i)	(conf.int)		5% VaR(X^bank i)	5% CoVaR^SWE|bank i	5% ΔCoVaR^SWE|bank i
8601 JT	-0.047	-0.054	-0.044	0.245	0.200	0.301	-7.1%	-6.4%	-1.7%
8604 JT	-0.046	-0.052	-0.042	0.252	0.190	0.272	-7.8%	-6.6%	-1.9%
ALBK ID	-0.051	-0.059	-0.044	0.006	-0.006	0.006	-11.3%	-5.1%	-0.1%
BAC UN	-0.041	-0.046	-0.036	0.327	0.307	0.339	-8.1%	-6.8%	-2.7%
BARC LN	-0.041	-0.046	-0.036	0.284	0.243	0.394	-7.7%	-6.3%	-2.2%
BBT UN	-0.046	-0.057	-0.041	0.296	0.164	0.365	-6.7%	-6.6%	-2.0%
BBVA SM	-0.039	-0.042	-0.035	0.482	0.431	0.506	-7.0%	-7.3%	-3.4%
BK UN	-0.045	-0.047	-0.041	0.330	0.268	0.372	-6.7%	-6.7%	-2.2%
BMO CN	-0.049	-0.058	-0.046	0.307	0.210	0.389	-4.7%	-6.4%	-1.5%
BMPS IM	-0.045	-0.049	-0.037	0.413	0.313	0.482	-7.2%	-7.4%	-2.9%
BNP FP	-0.038	-0.042	-0.036	0.506	0.424	0.546	-7.5%	-7.6%	-3.9%
BNS CT	-0.053	-0.058	-0.047	0.313	0.306	0.436	-4.8%	-6.8%	-1.6%
BTO SM	-0.041	-0.051	-0.038	0.453	0.342	0.565	-5.1%	-6.4%	-2.2%
C US	-0.044	-0.051	-0.038	0.300	0.241	0.305	-8.2%	-6.8%	-2.5%
CBA AU	-0.046	-0.053	-0.041	0.447	0.363	0.573	-4.5%	-6.6%	-2.2%
CBK GR	-0.042	-0.046	-0.035	0.352	0.296	0.362	-8.5%	-7.2%	-3.0%
CM CT	-0.048	-0.058	-0.042	0.386	0.279	0.541	-5.5%	-6.9%	-2.2%
COF UN	-0.046	-0.053	-0.043	0.262	0.216	0.312	-8.0%	-6.7%	-2.1%
CSGN VX	-0.038	-0.045	-0.036	0.361	0.328	0.480	-7.5%	-6.5%	-2.7%
DANSKE DC	-0.042	-0.050	-0.037	0.324	0.262	0.353	-5.8%	-6.1%	-1.9%
DBK GR	-0.036	-0.040	-0.032	0.458	0.400	0.497	-7.1%	-6.9%	-3.3%
EBS AV	-0.043	-0.048	-0.039	0.345	0.257	0.385	-7.7%	-7.0%	-2.7%
GLE FP	-0.036	-0.041	-0.032	0.393	0.370	0.439	-9.4%	-7.3%	-3.7%
GS UN	-0.045	-0.051	-0.039	0.325	0.278	0.411	-7.0%	-6.7%	-2.3%
INGA NA	-0.037	-0.044	-0.034	0.376	0.283	0.439	-9.4%	-7.2%	-3.7%
ISP IM	-0.041	-0.044	-0.039	0.387	0.369	0.435	-9.4%	-7.8%	-3.6%
JPM US	-0.043	-0.048	-0.039	0.355	0.307	0.397	-7.4%	-7.0%	-2.6%
LLOY LN	-0.044	-0.049	-0.039	0.191	0.190	0.197	-7.7%	-5.9%	-1.5%
MS UN	-0.042	-0.046	-0.038	0.282	0.260	0.310	-8.6%	-6.7%	-2.5%
NAB AU	-0.048	-0.054	-0.044	0.404	0.351	0.470	-5.4%	-7.0%	-2.4%
PNC UN	-0.045	-0.053	-0.041	0.349	0.272	0.368	-6.2%	-6.6%	-2.2%
POP SM	-0.045	-0.048	-0.041	0.414	0.340	0.494	-5.8%	-6.9%	-2.4%
RY CT	-0.053	-0.060	-0.046	0.322	0.244	0.547	-4.6%	-6.8%	-1.6%
SAN SM	-0.040	-0.045	-0.038	0.486	0.445	0.542	-6.9%	-7.4%	-3.4%
SLM US	-0.049	-0.056	-0.043	0.132	0.099	0.222	-7.3%	-5.9%	-1.0%
STAN LN	-0.044	-0.049	-0.038	0.481	0.392	0.538	-5.5%	-7.1%	-2.7%
STI UN	-0.047	-0.053	-0.040	0.269	0.190	0.355	-7.2%	-6.6%	-1.9%
STT UN	-0.046	-0.049	-0.043	0.270	0.260	0.331	-7.2%	-6.5%	-2.0%
TD CT	-0.053	-0.060	-0.045	0.276	0.231	0.468	-5.1%	-6.7%	-1.5%
UBSN VX	-0.044	-0.048	-0.038	0.309	0.251	0.354	-7.6%	-6.8%	-2.3%
UCG IM	-0.038	-0.043	-0.036	0.452	0.374	0.544	-7.9%	-7.4%	-3.7%
USB US	-0.049	-0.055	-0.044	0.305	0.255	0.383	-6.5%	-6.9%	-2.0%
WBC AU	-0.047	-0.055	-0.043	0.433	0.363	0.482	-4.9%	-6.8%	-2.3%
WFC UN	-0.047	-0.053	-0.044	0.339	0.320	0.410	-6.3%	-6.9%	-2.2%
					max		-11.3%	-7.8%	-3.9%
					min		-4.5%	-5.1%	-0.1%
					average		-7.0%	-6.8%	-2.4%
					median		-7.1%	-6.8%	-2.3%

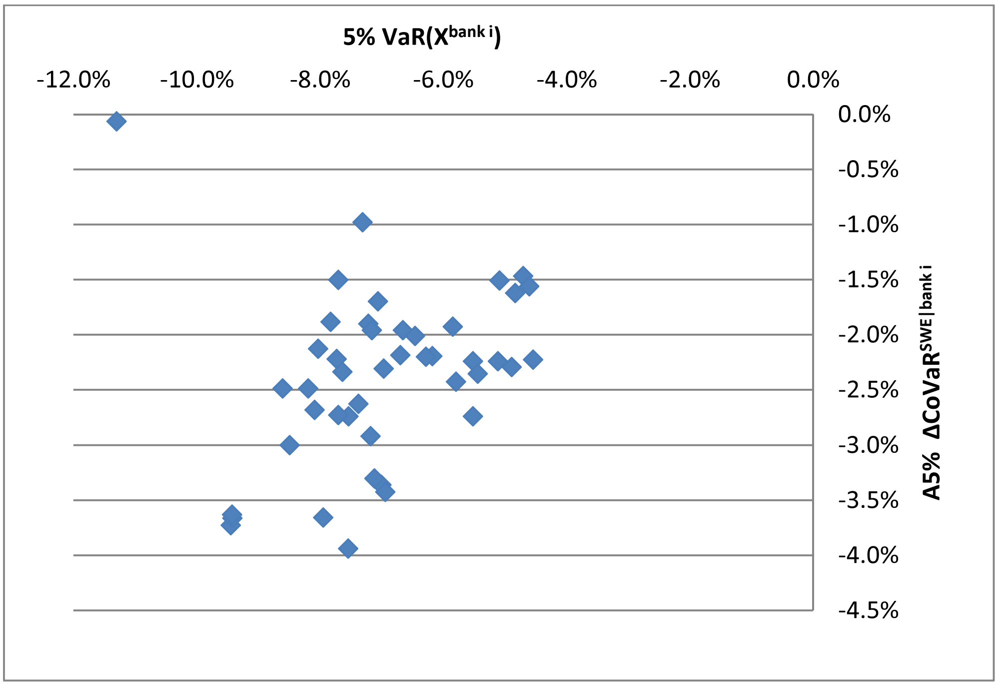


Figure 11 – 5%VaR of bank i as a function of 5%$\Delta CoVaR^{SWE|bank\ i}$

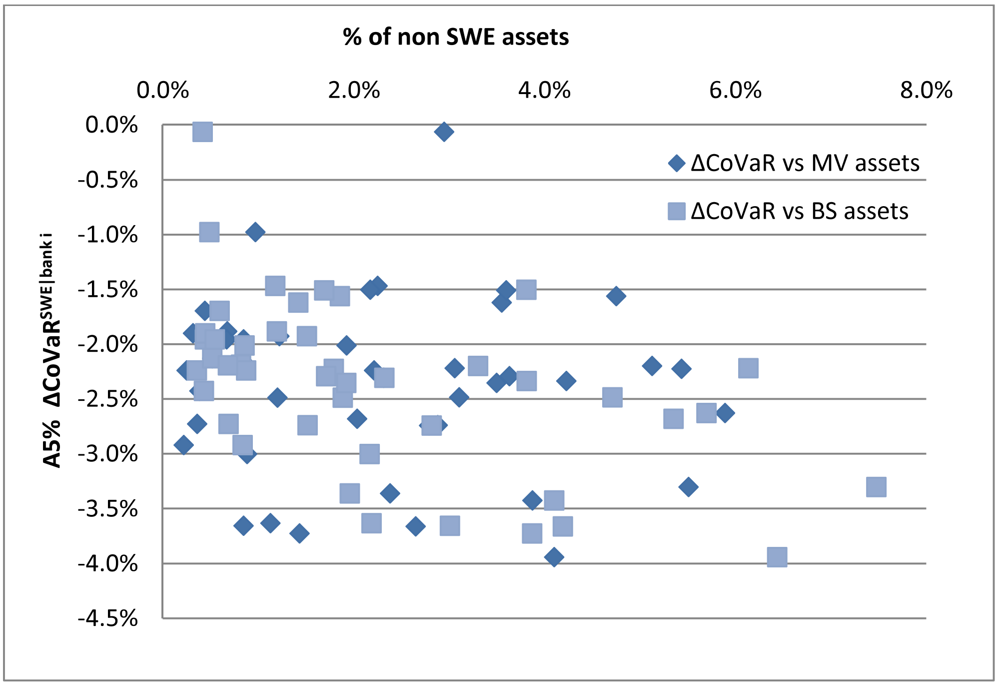


Figure 12 – Relative size of bank i as a function of 5%$\Delta CoVaR^{SWE|bank\ i}$

As well as looking into how the Swedish banking system is affected by each of the non-Swedish banks when they go into distress, a similar analysis on how each Swedish bank is affected each non-Swedish bank can be found in the Appendix (A5). Here (table 18) is instead a summary analysis of that, i.e. how much the system of non-Swedish banks can contribute to the risk of each Swedish bank. The system of non-Swedish banks (X^{nonSWE}) is calculated in the same way as X^{SWE}.

$$X_5^i = \alpha_5^i + \beta_5^i X^{nonSWE} + \varepsilon$$

By comparing the values of 5% $\Delta\text{CoVaR}^{\text{bank i|nonSWE}}$ it can be concluded that Handelsbanken (SHBA) is more stable than the other Swedish banks when the worldwide financial system goes into distress.

Table 18 - CoVaR and ΔCoVaR of each Swedish bank conditional on the system of non-Swedish banks

bank i|nonSWE	α	(conf.int)		β (X^{nonSWE})	(conf.int)		5% $\text{CoVaR}^{\text{bank i\| nonSWE}}$	5% $\Delta\text{CoVaR}^{\text{bank i\| nonSWE}}$
NDA SS	-0.041	-0.045	-0.037	0.875	0.686	0.889	-8.8%	-4.9%
SEBA SS	-0.046	-0.049	-0.043	0.923	0.743	1.031	-9.6%	-5.2%
SHBA SS	-0.037	-0.040	-0.032	0.636	0.435	0.783	-7.2%	-3.6%
SWEDA SS	-0.050	-0.054	-0.045	0.788	0.767	0.902	-9.3%	-4.4%

5.2.2 The final CoVaR model

Now moving on to the regression model used in section 5.1.4, first looking at how the Swedish banking system is affected by each non-Swedish bank i described by the following equation:

$$X_5^{SWE} = \alpha_5^i + \beta(-)_5^i X^i I_{(X^i<0)} + \beta(+)_5^i X^i I_{(X^i>0)} + \beta(vol)_5^i X^{vol}$$

Table 19 shows the regression parameters and their confidence intervals. The next table presents an example of $\text{CoVaR}^{\text{SWE|bank i}}$ and $\Delta\text{CoVaR}^{\text{SWE|bank i}}$ calculated using the regression parameters and assuming the same scenario as in section 5.1.4, i.e. that the asset growth rate of bank i is negative ($X^i < 0$) and that equity markets are volatile (by using the 75$^{\text{th}}$ quantile of the volatility index, X_{75}^{vol}).

Table 21 – The quantile regression parameters when regressing the Swedish banking system on each non-Swedish bank i

SWE|bank i	α	(conf.int)		β (X^i<0)	(conf.int)		β (X^i>0)	(conf.int)		β (vol)	(conf.int)	
8601 JT	-0.005	-0.015	0.016	0.319	0.162	0.475	0.173	-0.040	0.241	-0.00141	-0.00212	-0.00101
8604 JT	-0.003	-0.011	0.017	0.302	0.219	0.554	0.064	-0.100	0.176	-0.00130	-0.00232	-0.00102
ALBK ID	-0.002	-0.012	0.011	0.240	0.143	0.570	0.004	######	0.004	-0.00123	-0.00164	-0.00100
BAC UN	-0.004	-0.016	0.005	0.308	0.291	0.591	0.206	-0.081	0.312	-0.00129	-0.00161	-0.00057
BARC LN	-0.001	-0.009	0.008	0.402	0.301	0.761	0.214	0.059	0.287	-0.00137	-0.00178	-0.00079
BBT UN	0.003	-0.005	0.020	0.566	0.337	1.215	-0.115	-0.248	-0.028	-0.00142	-0.00209	-0.00110
BBVA SM	-0.005	-0.013	0.005	0.759	0.659	0.883	0.095	-0.275	0.201	-0.00081	-0.00162	-0.00051
BK UN	0.002	-0.008	0.009	0.547	0.338	1.044	-0.041	-0.085	0.044	-0.00144	-0.00198	-0.00077
BMO CN	-0.003	-0.011	0.007	0.622	0.333	1.406	-0.005	-0.135	0.102	-0.00132	-0.00181	-0.00089
BMPS IM	0.005	-0.002	0.012	0.663	0.443	0.944	0.099	-0.010	0.265	-0.00140	-0.00181	-0.00117
BNP FP	-0.010	-0.020	0.001	0.406	0.382	0.824	0.507	0.148	0.656	-0.00118	-0.00163	-0.00073
BNS CT	-0.004	-0.015	0.007	0.801	0.380	1.174	0.016	-0.145	0.083	-0.00125	-0.00160	-0.00086
BTO SM	0.006	-0.006	0.013	0.566	0.409	0.669	0.017	-0.124	0.232	-0.00157	-0.00184	-0.00130
C US	-0.007	-0.009	0.003	0.404	0.348	0.707	0.090	-0.132	0.157	-0.00098	-0.00143	-0.00091
CBA AU	-0.004	-0.013	0.006	1.178	0.550	1.506	-0.017	-0.078	0.155	-0.00108	-0.00184	-0.00074
CBK GR	-0.005	-0.018	0.009	0.601	0.457	0.644	0.073	-0.151	0.185	-0.00092	-0.00162	-0.00036
CM CT	-0.001	-0.016	0.010	0.816	0.412	0.948	-0.010	-0.139	0.121	-0.00130	-0.00174	-0.00092
COF UN	0.004	-0.006	0.011	0.461	0.284	0.634	0.060	-0.272	0.132	-0.00152	-0.00192	-0.00098
CSGN VX	-0.004	-0.016	0.006	0.677	0.511	0.795	0.146	-0.292	0.258	-0.00089	-0.00180	-0.00056
DANSKE DC	0.001	-0.014	0.010	0.807	0.403	1.141	0.073	-0.355	0.130	-0.00124	-0.00171	-0.00049
DBK GR	0.000	-0.011	0.004	0.564	0.495	0.705	0.157	-0.051	0.413	-0.00117	-0.00125	-0.00075
EBS AV	-0.003	-0.012	0.002	0.447	0.400	0.634	0.238	0.007	0.277	-0.00127	-0.00150	-0.00083
GLE FP	0.004	-0.011	0.008	0.549	0.331	0.677	0.203	0.115	0.395	-0.00144	-0.00158	-0.00084
GS UN	0.000	-0.009	0.009	0.511	0.378	0.857	0.127	0.007	0.197	-0.00141	-0.00162	-0.00101
INGA NA	-0.006	-0.015	0.007	0.408	0.359	0.598	0.262	0.153	0.292	-0.00120	-0.00174	-0.00075
ISP IM	-0.009	-0.028	0.008	0.555	0.348	0.845	0.173	0.093	0.260	-0.00097	-0.00177	-0.00031
JPM US	-0.004	-0.010	0.008	0.645	0.384	1.104	0.081	-0.139	0.101	-0.00105	-0.00153	-0.00063
LLOY LN	0.001	-0.008	0.006	0.298	0.211	0.404	0.210	0.002	0.210	-0.00154	-0.00185	-0.00106
MS UN	-0.002	-0.011	0.007	0.485	0.266	0.646	0.038	-0.231	0.182	-0.00109	-0.00185	-0.00085
NAB AU	-0.004	-0.011	0.007	0.678	0.540	0.912	0.123	-0.004	0.194	-0.00132	-0.00203	-0.00110
PNC UN	0.001	-0.008	0.008	0.504	0.331	0.818	-0.036	-0.180	0.091	-0.00134	-0.00178	-0.00076
POP SM	0.007	-0.004	0.012	0.857	0.424	1.022	-0.007	-0.371	0.206	-0.00148	-0.00199	-0.00117
RY CT	-0.001	-0.011	0.008	0.731	0.690	1.218	-0.042	-0.156	0.084	-0.00132	-0.00177	-0.00098
SAN SM	-0.005	-0.016	0.012	0.770	0.521	1.001	0.191	-0.150	0.368	-0.00096	-0.00185	-0.00046
SLM US	0.001	-0.007	0.012	0.320	0.194	0.602	-0.014	-0.474	0.129	-0.00157	-0.00225	-0.00123
STAN LN	0.006	-0.014	0.015	0.779	0.546	0.982	0.144	-0.218	0.257	-0.00145	-0.00191	-0.00070
STI UN	-0.001	-0.007	0.004	0.401	0.331	0.637	0.028	-0.309	0.031	-0.00139	-0.00160	-0.00107
STT UN	-0.002	-0.016	0.010	0.550	0.362	0.796	-0.014	-0.196	0.088	-0.00124	-0.00164	-0.00074
TD CT	-0.003	-0.014	0.009	0.746	0.412	0.861	0.020	-0.164	0.143	-0.00128	-0.00183	-0.00086
UBSN VX	0.008	-0.008	0.013	0.508	0.271	1.080	0.175	-0.202	0.265	-0.00173	-0.00182	-0.00095
UCG IM	-0.005	-0.025	0.012	0.570	0.475	0.914	0.216	-0.165	0.290	-0.00107	-0.00173	-0.00034
USB US	-0.002	-0.010	0.006	0.458	0.398	0.996	0.022	-0.232	0.093	-0.00131	-0.00184	-0.00100
WBC AU	0.000	-0.012	0.008	0.911	0.694	1.203	0.024	-0.104	0.260	-0.00133	-0.00169	-0.00095
WFC UN	-0.002	-0.009	0.005	0.623	0.390	0.962	-0.048	-0.211	0.168	-0.00126	-0.00178	-0.00109

Table 22 - - CoVaR and ΔCoVaR of the Swedish banking system conditional on non-Swedish bank i

SWE|bank i	5% $CoVaR^{SWE\|bank\ i}$	5% $\Delta CoVaR^{SWE\|bank\ i}$
8601 JT	-6.9%	-2.2%
8604 JT	-6.5%	-2.3%
ALBK ID	-6.6%	-2.7%
BAC UN	-6.7%	-2.5%
BARC LN	-7.3%	-3.1%
BBT UN	-7.7%	-3.7%
BBVA SM	-8.3%	-5.3%
BK UN	-7.7%	-3.6%
BMO CN	-7.1%	-3.0%
BMPS IM	-8.4%	-4.7%
BNP FP	-7.5%	-3.2%
BNS CT	-7.9%	-4.1%
BTO SM	-7.0%	-2.8%
C US	-6.9%	-3.3%
CBA AU	-8.9%	-5.9%
CBK GR	-8.3%	-5.1%
CM CT	-8.4%	-4.7%
COF UN	-7.9%	-3.7%
CSGN VX	-8.1%	-5.1%
DANSKE DC	-8.3%	-4.8%
DBK GR	-7.5%	-4.1%
EBS AV	-7.5%	-3.5%
GLE FP	-9.1%	-5.2%
GS UN	-7.8%	-3.6%
INGA NA	-8.0%	-4.0%
ISP IM	-9.0%	-5.2%
JPM US	-8.2%	-4.8%
LLOY LN	-6.7%	-2.3%
MS UN	-7.7%	-4.3%
NAB AU	-8.0%	-3.9%
PNC UN	-7.0%	-3.2%
POP SM	-8.6%	-5.0%
RY CT	-7.3%	-3.5%
SAN SM	-8.7%	-5.4%
SLM US	-6.8%	-2.4%
STAN LN	-8.0%	-4.4%
STI UN	-7.1%	-2.8%
STT UN	-7.8%	-4.0%
TD CT	-7.9%	-4.1%
UBSN VX	-8.2%	-3.8%
UCG IM	-8.2%	-4.6%
USB US	-7.0%	-3.0%
WBC AU	-8.4%	-4.8%
WFC UN	-7.8%	-4.0%
max	-9.1%	-5.9%
min	-6.5%	-2.2%
average	-7.7%	-3.9%
median	-7.8%	-4.0%

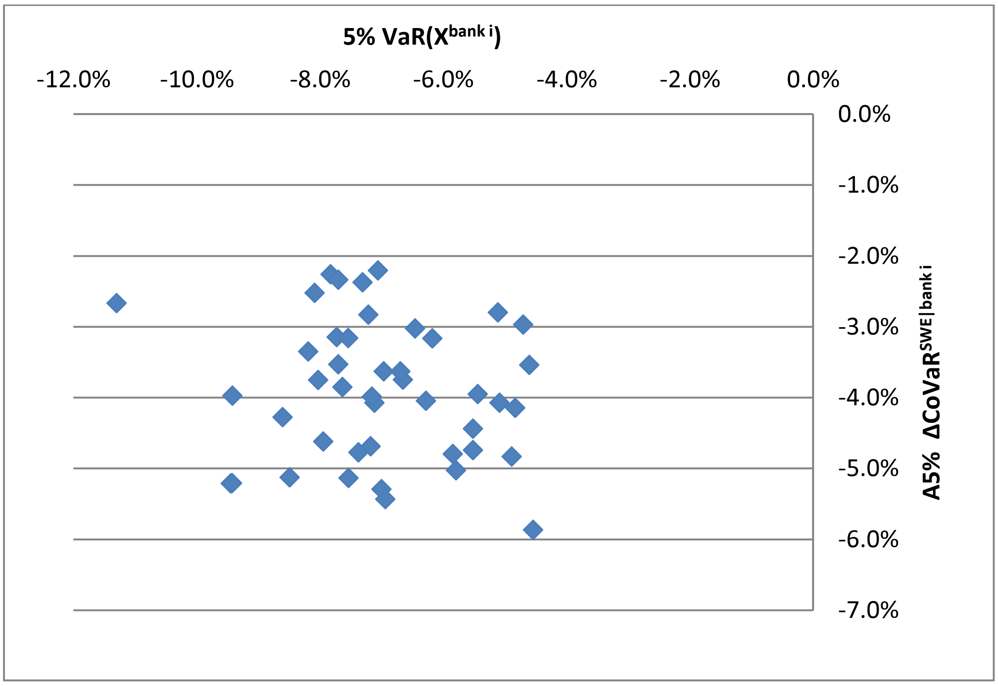


Figure 13 - 5%VaR of bank i as a function of 5%ΔCoVaR$^{SWE|bank\ i}$

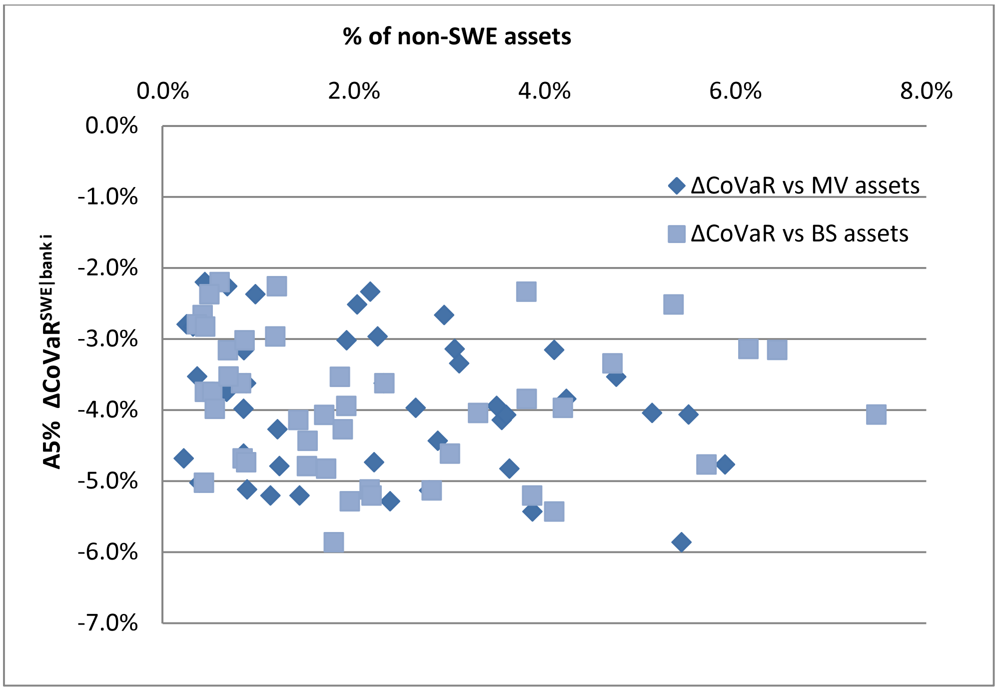


Figure 14 – Relative size of bank i as a function of 5%ΔCoVaR$^{SWE|bank\ i}$

Results describing how each Swedish bank is affected by the system of non-Swedish banks under the same scenario can be found in table 21 and table 22, according to the following equation:

$$X_5^i = \alpha_5^{nonSWE} + \beta(-)_5^{nonSWE} X^{nonSWE} I_{(X^{nonSWE}<0)} + \beta(+)_5^{nonSWE} X^{nonSWE} I_{(X^{nonSWE}>0)} + \beta(vol)_5^{nonSWE} X^{vol}$$

Again, the ΔCoVaR results indicate that Handelsbanken is a more stable bank than the others. Here and in section 5.2.1, SEB is more sensitive than the other banks to the worldwide financial system going into distress.

Table 21 - CoVaR and ΔCoVaR of each Swedish bank conditional on the system of non-Swedish banks

bank i|nonSWE	α	(conf.int)		β (X^i<0)	(conf.int)		β (X^i>0)	(conf.int)		β (vol)	(conf.int)	
NDA SS	-0.016	-0.024	-0.003	0.954	0.734	1.757	0.263	-0.354	0.591	-0.001	-0.001	0.000
SEBA SS	-0.008	-0.017	0.013	1.152	0.972	1.670	0.191	-0.076	0.715	-0.001	-0.002	-0.001
SHBA SS	-0.009	-0.020	0.000	0.799	0.388	1.127	0.341	-0.166	0.411	-0.001	-0.001	0.000
SWEDA SS	0.003	-0.005	0.008	1.046	0.703	1.417	0.282	-0.113	0.742	-0.002	-0.002	-0.001

Table 22 - CoVaR and ΔCoVaR of each Swedish bank conditional on the system of non-Swedish banks

bank i|nonSWE	5% CoVaR$^{\text{bank i}\|\text{system}}$	5% ΔCoVaR$^{\text{bank i}\|\text{system}}$
NDA SS	-8.2%	-5.3%
SEBA SS	-10.1%	-6.2%
SHBA SS	-7.8%	-4.6%
SWEDA SS	-10.4%	-5.1%

5.2.3 Different windows - Before and after crisis

Finally is a comparison of the CoVaR results for two different time frames as done in section 5.1.5, but now for the larger set of international banks. An analysis of the Swedish system CoVaR conditional on each non-Swedish bank (CoVaR$^{\text{SWE}|\text{bank i}}$ and ΔCoVaR$^{\text{SWE}|\text{bank i}}$) is presented in table 23. The regression parameters suggest in general a stronger relationship between the Swedish system and the non-Swedish banks in the second period and a hence larger spillover risk. A summary of the results is at the bottom of the table showing that the average ΔCoVaR$^{\text{SWE}|\text{bank i}}$ is -1,5% in the second period but -0,6% in the first period. This is in accordance to previous results for these two time frames where the spillover risk is most often larger during the more volatile second period.

Table 23 - Comparison of CoVaR and ΔCoVaR of the Swedish banking system conditional on each non-Swedish bank i , from different data

	Before 1.1.2008				From 1.1.2008			
	α	$\beta(X^i)$	5% CoVaR	5% ΔCoVaR	α	$\beta(X^i)$	5% CoVaR	5% ΔCoVaR
8601 JT	-0,024	0,122	-3,0%	-0,5%	-0,041	0,114	-4,7%	-0,5%
8604 JT	-0,024	0,115	-2,8%	-0,5%	-0,041	0,158	-4,9%	-0,7%
ALBK ID	-0,023	0,214	-3,2%	-0,9%	-0,041	0,012	-4,2%	-0,1%
BAC UN	-0,024	0,135	-3,0%	-0,6%	-0,035	0,168	-5,2%	-1,6%
BARC LN	-0,022	0,266	-3,4%	-1,1%	-0,033	0,279	-5,2%	-1,8%
BBT UN	-0,024	0,085	-2,7%	-0,3%	-0,038	0,160	-5,0%	-1,1%
BBVA SM	-0,024	0,272	-3,4%	-1,0%	-0,035	0,358	-5,5%	-2,1%
BK UN	-0,024	0,140	-3,0%	-0,6%	-0,040	0,152	-5,0%	-1,1%
BMO CN	-0,024	0,092	-2,8%	-0,3%	-0,040	0,361	-5,3%	-1,3%
BMPS IM	-0,024	0,232	-3,2%	-0,9%	-0,037	0,322	-5,5%	-1,7%
BNP FP	-0,023	0,284	-3,4%	-1,1%	-0,033	0,322	-5,5%	-2,2%
BNS CT	-0,025	0,085	-2,7%	-0,3%	-0,039	0,324	-5,1%	-1,2%
BTO SM	-0,024	0,155	-2,9%	-0,5%	-0,037	0,333	-5,3%	-1,5%
C US	-0,024	0,146	-3,1%	-0,7%	-0,037	0,152	-5,1%	-1,4%
CBA AU	-0,024	0,052	-2,5%	-0,2%	-0,042	0,033	-4,3%	-0,1%
CBK GR	-0,023	0,248	-3,4%	-1,1%	-0,034	0,318	-5,7%	-2,2%
CM CT	-0,024	0,094	-2,8%	-0,3%	-0,040	0,324	-5,3%	-1,2%
COF UN	-0,024	0,092	-3,0%	-0,5%	-0,037	0,165	-5,1%	-1,4%
CSGN VX	-0,024	0,192	-3,3%	-0,9%	-0,036	0,335	-5,9%	-2,2%
DANSKE DC	-0,024	0,033	-2,5%	-0,1%	-0,034	0,452	-5,5%	-2,1%
DBK GR	-0,023	0,265	-3,4%	-1,2%	-0,033	0,309	-5,4%	-2,0%
EBS AV	-0,024	0,216	-3,2%	-0,8%	-0,034	0,299	-5,6%	-2,2%
GLE FP	-0,023	0,258	-3,4%	-1,1%	-0,033	0,296	-5,5%	-2,1%
GS UN	-0,024	0,128	-3,0%	-0,6%	-0,040	0,266	-6,0%	-2,0%
INGA NA	-0,023	0,254	-3,4%	-1,2%	-0,030	0,309	-5,6%	-2,5%
ISP IM	-0,023	0,214	-3,3%	-0,9%	-0,034	0,375	-6,1%	-2,7%
JPM US	-0,024	0,125	-3,0%	-0,6%	-0,038	0,165	-5,1%	-1,3%
LLOY LN	-0,023	0,239	-3,2%	-1,0%	-0,034	0,275	-5,5%	-2,1%
MS UN	-0,024	0,130	-3,1%	-0,7%	-0,039	0,195	-5,7%	-1,8%
NAB AU	-0,024	0,026	-2,5%	-0,1%	-0,041	0,093	-4,5%	-0,3%
PNC UN	-0,024	0,106	-2,8%	-0,4%	-0,037	0,157	-4,9%	-1,1%
POP SM	-0,024	0,188	-3,1%	-0,6%	-0,034	0,401	-5,5%	-2,1%
RY CT	-0,025	0,085	-2,7%	-0,3%	-0,039	0,326	-5,1%	-1,2%
SAN SM	-0,023	0,238	-3,3%	-1,0%	-0,034	0,368	-5,5%	-2,1%
SLM US	-0,025	0,125	-3,1%	-0,6%	-0,038	0,123	-5,0%	-1,2%
STAN LN	-0,024	0,261	-3,3%	-1,0%	-0,035	0,337	-5,5%	-2,0%
STI UN	-0,024	0,124	-2,9%	-0,5%	-0,037	0,168	-5,1%	-1,3%
STT UN	-0,024	0,130	-3,0%	-0,6%	-0,039	0,125	-4,8%	-1,0%
TD CT	-0,024	0,079	-2,7%	-0,3%	-0,041	0,350	-5,3%	-1,3%
UBSN VX	-0,023	0,195	-3,2%	-0,8%	-0,035	0,376	-5,9%	-2,4%
UCG IM	-0,023	0,255	-3,3%	-1,0%	-0,034	0,333	-5,8%	-2,4%
USB US	-0,024	0,103	-2,9%	-0,4%	-0,039	0,189	-5,3%	-1,4%
WBC AU	-0,024	0,032	-2,5%	-0,1%	-0,042	0,035	-4,3%	-0,1%
WFC UN	-0,025	0,132	-3,0%	-0,5%	-0,038	0,177	-5,2%	-1,4%
max	-0,022	0,284	-3,4%	-1,2%	-0,030	0,452	-6,1%	-2,7%
min	-0,025	0,026	-2,5%	-0,1%	-0,042	0,012	-4,2%	-0,1%
average	-0,024	0,158	-3,0%	-0,6%	-0,037	0,247	-5,3%	-1,5%
median	-0,024	0,133	-3,0%	-0,6%	-0,037	0,287	-5,3%	-1,5%

6 Conclusions

By now it is possible to draw conclusions on how helpful the CoVaR measure is to get a better understanding of how risk spreads through financial systems.

When analysing the Swedish banking system in its isolation it is interesting to note that according to the results, the four large Swedish banks all contribute similarly much to the risk of the system when using the models in section 5.1.1, 5.1.2 and 5.1.4. The contribution of each bank differs some more between each bank in section 5.1.2 but the general result of similar risk contribution to the system is regardless of each banks size or individual risk. When evaluating the risk contribution between the banks and the exposure risk of each bank to a distress in the system the result suggest that Handelsbanken is the most stable bank and less sensitive to distress in other banks or the system. SEB, and Swedbank are however by far more sensitive to outside stress than the Handelsbanken and Nordea.

Then there are few things worth noticing when estimating how the Swedish banking system can be affected by outside risk by adding to the analysis a number of international banks. It cannot be assumed that larger international banks contribute more to the risk of the Swedish banking system than smaller banks do and also it cannot be assumed that banks with high individual VaR contribute more to the risk of the Swedish banking system than banks with lower individual VaR. From this section it is also apparent that of the four Swedish banks, Handelsbanken seems to be the least sensitive to distress in other banks and again SEB and Swedbank are by far more sensitive than the other two.

It is not obvious that one particular version of the CoVaR model is the best version. It is rather an issue of preference and objective of the user. The model used in section 5.1.4 could be considered a good one by looking at the goodness of fit of the regression parameters, by how it is relatively simple and does not demand many assumptions to be made (e.g. what value of the volatility index to use when calculating CoVaR). It could be a good idea to actively run more than one version of the model when using CoVaR as a monitoring tool. Finally it needs to be kept in mind that the time frame of input data directly influences the results. Hence it could be wise to run the CoVaR model both for the longest time series available and also for rolling windows to see how worst case and best case results differ.

CoVaR is a systemic risk indicator that is easy to interpret, does not demand complicated data set and can be used with other risk indicators and stress tests that together help get a better understanding of the risks threatening the stability of the Swedish financial system.

7 Bibliography

[1] Group of Ten, "Report on Consolidation in the Financial Sector," Bank for International Settlements., Basel, Switzerland, 2001.

[2] T. Adrian and M. K. Brunnermeier, “CoVaR,” Federal Reserve Bank of New York Staff Reports, no. 348, September 2008; revised September 2011.

[3] R. Koenker, Quantile Regression (Econometric Society Monographs), Cambridge University Press, 2005.

[4] W. H. Greene, Econometric Analysis (7th Edition), Prentice Hall, 2011.

[5] R. Koenker and G. Basset Jr., "Regression Quantiles," *Econometrica,* vol. 46, no. 1, pp. 33-50, 1978.

[6] R. Koenker and K. F. Hallock, "Quantile Regression," *Journal of Economic Perspectives,* vol. 15, no. 4, pp. 143-156, 2001.

[7] A. Damodaran, "Damodaran Online - NYU Stern," [Online]. Available: http://people.stern.nyu.edu/adamodar/pdfiles/papers/VAR.pdf.

[8] P. Jorion, Value at Risk: The New Benchmark for Managing Financial Risk, 3rd Edition, McGraw-Hill, 2006.

[9] C. Acerbi and D. Tasche, "Expected Shortfall: a natural coherent alternative," *Journal of Banking & Finance,* vol. 26(7), p. 1487–1503, 2001.

[10] G. Lopez-Espinosa, A. Moreno, A. Rubia and L. Valderrama, "Short-term Wholesale Funding and Systemic Risk: A Global CoVaR Approach," International Monetary Fund, 2012.

[11] Z. Adams, R. Füss and R. Gropp, "Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk (SDSVaR) Approach," European Business School Research Paper No. 10-12. Available at SSRN: http://ssrn.com/abstract=1705997 or http://dx.doi.org/10.2139/ssrn.1705997, January 2010, revised March 2011.

[12] C. Gutenbrunner and J. Jureckova, "Regression Rank Scores and Regression Quantiles," *The Annals of Statistics,* vol. 20, no. 1, pp. 305-330, 1992.

[13] "SAS Institute. The Power to Know - SAS/STAT(R) 9.22 User's Guide," SAS Institute Inc., 2012. [Online]. Available: http://support.sas.com/documentation/cdl/en/statug/63347/HTML/default/viewer.htm#qreg_toc.htm.

Appendix

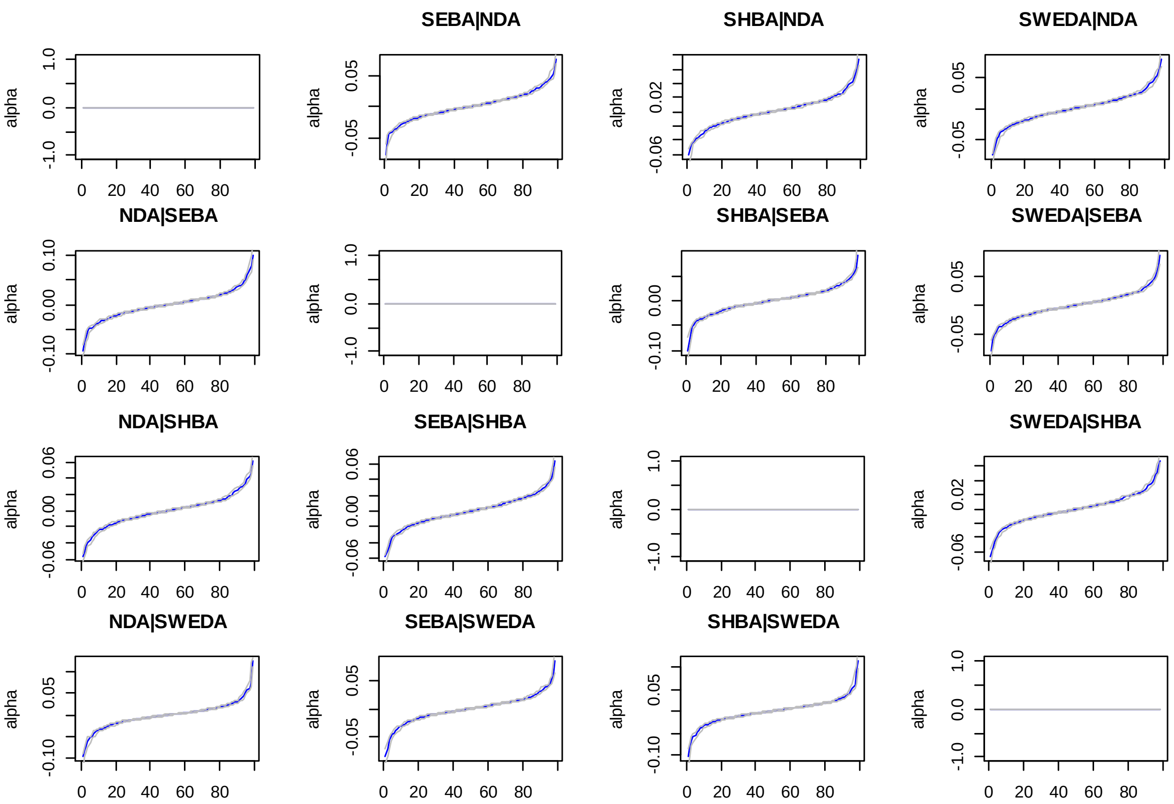
A1 Confidence Intervals:

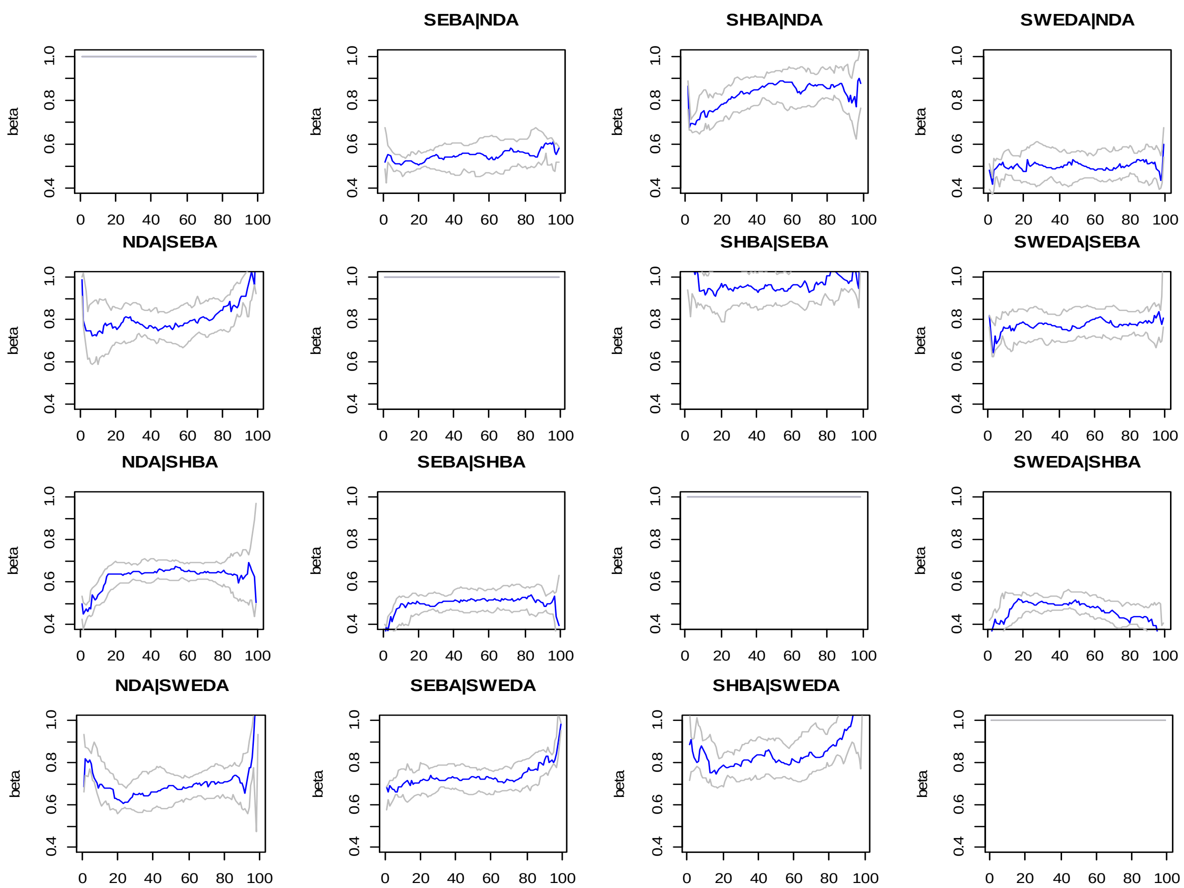
The method used here to compute confidence intervals for the quantile regression parameters is called the rank method and is based on inversion of the rank score test. The classical theory of rank tests is covered in detail by Gutenbrunner and Jureckova [12]. The rank test can be used to test the hypothesis: $H_0 \colon \beta = \eta$ in the linear regression model $y = \alpha + \beta X + \varepsilon$. Confidence intervals for the quantiles corresponding to the regression parameter β can be found by inverting this test [13]. The rank method uses the simplex algorithm for computation. The rank method and other methods to compute confidence intervals for quantile regression parameters are described in detail by Koenker [3].

A2 List of banks:

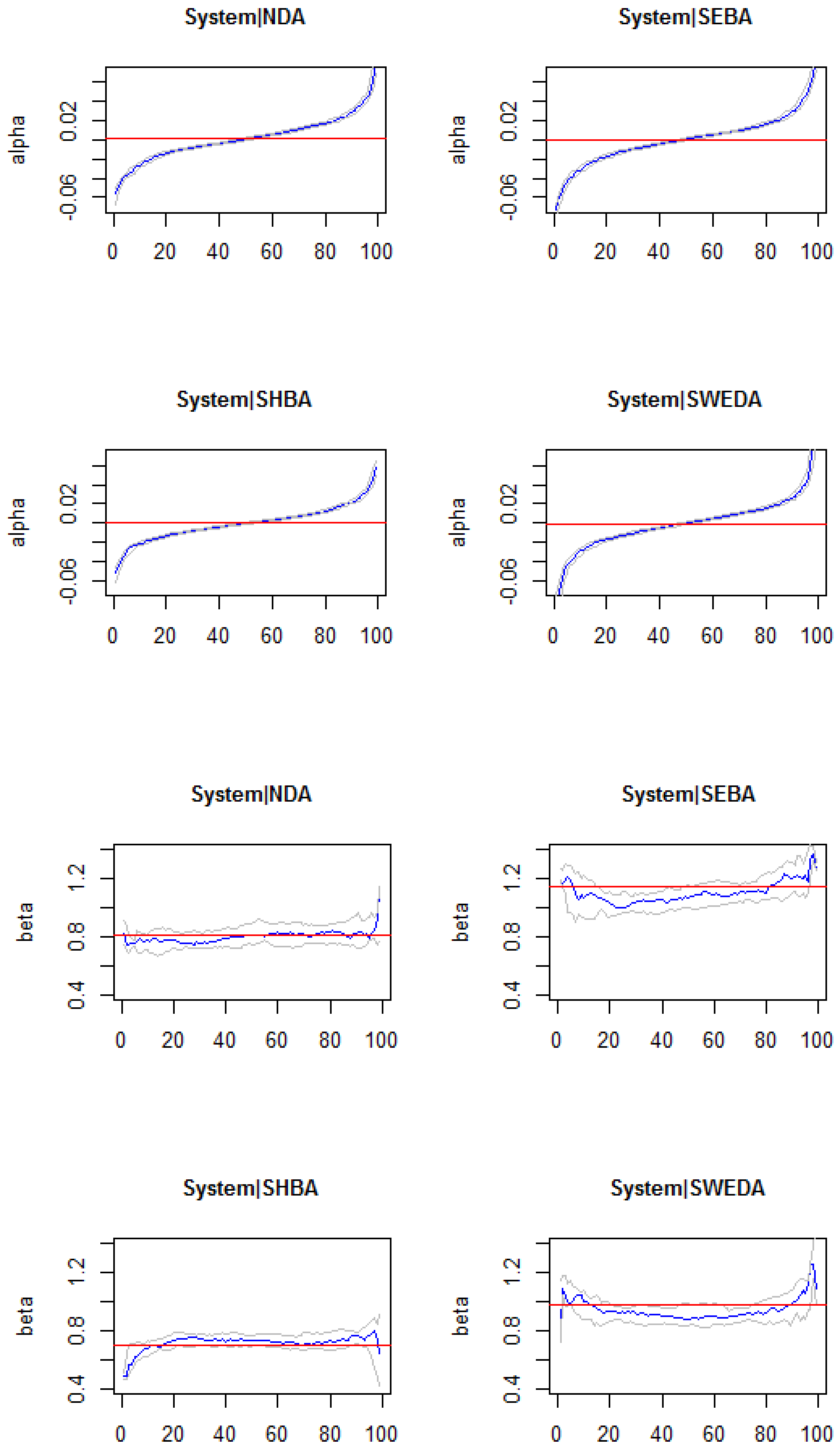
NDA SS	Nordea Bank AB
SEBA SS	Skandinaviska Enskilda Banken AB
SHBA SS	Svenska Handelsbanken AB
SWEDA SS	Swedbank AB
8601 JT	Daiwa Securities Group Inc
8604 JT	Nomura Holdings Inc
ALBK ID	Allied Irish Banks PLC
BAC UN	Bank of America Corp
BARC LN	Barclays PLC
BBT UN	BB&T Corp
BBVA SM	Banco Bilbao Vizcaya Argentaria SA
BK UN	Company Profile for Bank of New York Mellon Corp
BMO CN	Bank of Montreal
BMPS IM	Banca Monte dei Paschi di Siena SpA
BNP FP	BNP Paribas SA
BNS CT	Bank of Nova Scotia
BTO SM	Banco Espanol de Credito SA
C US	Citigroup Inc
CBA AU	Commonwealth Bank of Australia
CBK GR	Commerzbank AG
CM CT	Canadian Imperial Bank of Commerce/Canada
COF UN	Capital One Financial Corp
CSGN VX	Credit Suisse Group AG
DANSKE DC	Danske Bank A/S
DBK GR	Deutsche Bank AG
EBS AV	Erste Group Bank AG
GLE FP	Societe Generale SA
GS UN	Goldman Sachs Group Inc/The
INGA NA	ING Groep NV
ISP IM	Intesa Sanpaolo SpA
JPM US	JPMorgan Chase & Co
LLOY LN	Lloyds Banking Group PLC
MS UN	Morgan Stanley
NAB AU	National Australia Bank Ltd
PNC UN	PNC Financial Services Group Inc
POP SM	Banco Popular Espanol SA
RY CT	Royal Bank of Canada
SAN SM	Banco Santander SA
SLM UN	SLM Corp
STAN LN	Standard Chartered PLC
STI UN	SunTrust Banks Inc
STT UN	State Street Corp
TD CT	Toronto-Dominion Bank/The
UBSN VX	UBS AG
UCG IM	UniCredit SpA
USB US	US Bancorp
WBC AU	Westpac Banking Corp
WFC UN	Wells Fargo & Co

A3 $\text{CoVaR}^{\text{bank } j \mid \text{bank } l}$ parameters from the original CoVaR model





A4 $CoVaR^{bank\ i|system}$ parameters from the original CoVaR model



A5

NDA|bank i	α	(conf.int)		β (X^i)	(conf.int)		5% VaR($X^{bank\ i}$)	5% CoVaR$^{NDA\|bank\ i}$	5% ΔCoVaR$^{NDA\|bank\ i}$
NDA SS									
SEBA SS	-0.037	-0.042	-0.035	0.526	0.509	0.563	-6.7%	-7.2%	-3.6%
SHBA SS	-0.037	-0.042	-0.034	0.728	0.653	0.824	-4.7%	-7.1%	-3.5%
SWEDA SS	-0.043	-0.052	-0.037	0.497	0.437	0.538	-6.9%	-7.7%	-3.5%
8601 JT	-0.052	-0.057	-0.048	0.293	0.262	0.327	-7.1%	-7.3%	-2.0%
8604 JT	-0.051	-0.056	-0.044	0.267	0.231	0.333	-7.8%	-7.2%	-2.0%
ALBK ID	-0.055	-0.063	-0.046	0.006	-0.110	0.006	-11.3%	-5.6%	-0.1%
BAC UN	-0.049	-0.053	-0.042	0.317	0.304	0.333	-8.1%	-7.5%	-2.6%
BARC LN	-0.043	-0.053	-0.039	0.323	0.224	0.384	-7.7%	-6.8%	-2.5%
BBT UN	-0.051	-0.063	-0.046	0.223	0.120	0.352	-6.7%	-6.6%	-1.5%
BBVA SM	-0.041	-0.047	-0.037	0.503	0.453	0.547	-7.0%	-7.6%	-3.5%
BK UN	-0.051	-0.054	-0.046	0.362	0.304	0.430	-6.7%	-7.5%	-2.4%
BMO CN	-0.054	-0.059	-0.047	0.337	0.284	0.450	-4.7%	-7.0%	-1.6%
BMPS IM	-0.049	-0.057	-0.043	0.393	0.267	0.443	-7.2%	-7.7%	-2.8%
BNP FP	-0.041	-0.044	-0.037	0.459	0.393	0.531	-7.5%	-7.6%	-3.6%
BNS CT	-0.056	-0.062	-0.050	0.417	0.327	0.494	-4.8%	-7.6%	-2.2%
BTO SM	-0.048	-0.057	-0.040	0.425	0.276	0.652	-5.1%	-7.0%	-2.1%
C US	-0.051	-0.053	-0.044	0.295	0.281	0.317	-8.2%	-7.5%	-2.4%
CBA AU	-0.052	-0.057	-0.046	0.443	0.389	0.521	-4.5%	-7.2%	-2.2%
CBK GR	-0.043	-0.048	-0.039	0.315	0.280	0.349	-8.5%	-7.0%	-2.7%
CM CT	-0.053	-0.059	-0.046	0.441	0.350	0.582	-5.5%	-7.7%	-2.6%
COF UN	-0.052	-0.060	-0.048	0.279	0.238	0.355	-8.0%	-7.4%	-2.3%
CSGN VX	-0.044	-0.050	-0.038	0.497	0.375	0.559	-7.5%	-8.1%	-3.8%
DANSKE DC	-0.046	-0.054	-0.039	0.394	0.261	0.406	-5.8%	-6.9%	-2.3%
DBK GR	-0.040	-0.043	-0.037	0.468	0.426	0.524	-7.1%	-7.3%	-3.4%
EBS AV	-0.049	-0.055	-0.042	0.397	0.252	0.465	-7.7%	-7.9%	-3.1%
GLE FP	-0.040	-0.045	-0.036	0.411	0.390	0.499	-9.4%	-7.9%	-3.9%
GS UN	-0.050	-0.056	-0.044	0.342	0.266	0.408	-7.0%	-7.4%	-2.4%
INGA NA	-0.040	-0.046	-0.038	0.411	0.330	0.465	-9.4%	-7.9%	-4.0%
ISP IM	-0.044	-0.049	-0.039	0.412	0.344	0.498	-9.4%	-8.3%	-3.9%
JPM US	-0.049	-0.054	-0.044	0.374	0.303	0.429	-7.4%	-7.7%	-2.8%
LLOY LN	-0.051	-0.055	-0.040	0.183	0.182	0.207	-7.7%	-6.5%	-1.4%
MS UN	-0.049	-0.054	-0.044	0.297	0.257	0.331	-8.6%	-7.5%	-2.6%
NAB AU	-0.052	-0.060	-0.047	0.385	0.351	0.421	-5.4%	-7.3%	-2.2%
PNC UN	-0.054	-0.057	-0.045	0.341	0.295	0.351	-6.2%	-7.5%	-2.1%
POP SM	-0.048	-0.055	-0.043	0.433	0.214	0.539	-5.8%	-7.3%	-2.5%
RY CT	-0.056	-0.062	-0.045	0.483	0.330	0.619	-4.6%	-7.9%	-2.3%
SAN SM	-0.042	-0.047	-0.038	0.526	0.448	0.550	-6.9%	-7.8%	-3.7%
SLM US	-0.055	-0.062	-0.046	0.125	0.080	0.179	-7.3%	-6.4%	-0.9%
STAN LN	-0.045	-0.053	-0.042	0.483	0.384	0.593	-5.5%	-7.2%	-2.8%
STI UN	-0.050	-0.060	-0.045	0.251	0.182	0.358	-7.2%	-6.8%	-1.8%
STT UN	-0.050	-0.057	-0.044	0.303	0.256	0.371	-7.2%	-7.1%	-2.2%
TD CT	-0.056	-0.060	-0.046	0.372	0.316	0.456	-5.1%	-7.5%	-2.0%
UBSN VX	-0.050	-0.056	-0.042	0.285	0.258	0.387	-7.6%	-7.1%	-2.2%
UCG IM	-0.045	-0.048	-0.039	0.453	0.434	0.543	-7.9%	-8.1%	-3.7%
USB US	-0.054	-0.063	-0.047	0.333	0.194	0.386	-6.5%	-7.6%	-2.2%
WBC AU	-0.054	-0.063	-0.047	0.404	0.331	0.501	-4.9%	-7.4%	-2.1%
WFC UN	-0.052	-0.059	-0.046	0.364	0.317	0.438	-6.3%	-7.5%	-2.4%
					max		-11.3%	-8.3%	-4.0%
					min		-4.5%	-5.6%	-0.1%
					average		-6.9%	-7.4%	-2.6%
					median		-7.1%	-7.4%	-2.4%

SEBA|bank i	α	(conf.int)		β (X^i)	(conf.int)		5% VaR($X^{bank\ i}$)	5% CoVaR$^{SEB\|bank\ i}$	5% ΔCoVaR$^{SEB\|bank\ i}$
NDA SS	-0.051	-0.059	-0.046	0.703	0.629	0.844	-5.5%	-8.9%	-4.0%
SEBA SS									
SHBA SS	-0.043	-0.051	-0.041	1.058	0.910	1.201	-4.7%	-9.3%	-5.0%
SWEDA SS	-0.041	-0.048	-0.037	0.805	0.679	0.833	-6.9%	-9.7%	-5.7%
8601 JT	-0.063	-0.076	-0.055	0.258	0.159	0.334	-7.1%	-8.2%	-1.8%
8604 JT	-0.062	-0.072	-0.055	0.267	0.162	0.334	-7.8%	-8.3%	-2.0%
ALBK ID	-0.066	-0.077	-0.056	0.008	0.008	0.008	-11.3%	-6.7%	-0.1%
BAC UN	-0.057	-0.063	-0.048	0.481	0.385	0.523	-8.1%	-9.6%	-3.9%
BARC LN	-0.055	-0.059	-0.050	0.341	0.323	0.352	-7.7%	-8.1%	-2.7%
BBT UN	-0.061	-0.070	-0.058	0.299	0.220	0.338	-6.7%	-8.1%	-2.0%
BBVA SM	-0.054	-0.061	-0.049	0.604	0.491	0.708	-7.0%	-9.6%	-4.2%
BK UN	-0.058	-0.068	-0.055	0.295	0.270	0.367	-6.7%	-7.8%	-2.0%
BMO CN	-0.066	-0.075	-0.058	0.374	0.205	0.429	-4.7%	-8.4%	-1.8%
BMPS IM	-0.054	-0.062	-0.050	0.471	0.415	0.572	-7.2%	-8.8%	-3.3%
BNP FP	-0.052	-0.060	-0.047	0.543	0.440	0.648	-7.5%	-9.3%	-4.2%
BNS CT	-0.067	-0.076	-0.062	0.417	0.336	0.510	-4.8%	-8.8%	-2.2%
BTO SM	-0.059	-0.067	-0.050	0.472	0.401	0.687	-5.1%	-8.3%	-2.3%
C US	-0.055	-0.060	-0.053	0.302	0.245	0.365	-8.2%	-8.0%	-2.5%
CBA AU	-0.060	-0.070	-0.054	0.566	0.425	0.705	-4.5%	-8.6%	-2.8%
CBK GR	-0.051	-0.057	-0.047	0.452	0.399	0.488	-8.5%	-8.9%	-3.9%
CM CT	-0.062	-0.075	-0.058	0.453	0.311	0.572	-5.5%	-8.7%	-2.6%
COF UN	-0.062	-0.071	-0.054	0.297	0.230	0.342	-8.0%	-8.6%	-2.4%
CSGN VX	-0.053	-0.066	-0.048	0.448	0.302	0.495	-7.5%	-8.7%	-3.4%
DANSKE DC	-0.059	-0.065	-0.050	0.467	0.347	0.532	-5.8%	-8.7%	-2.8%
DBK GR	-0.050	-0.057	-0.042	0.575	0.397	0.677	-7.1%	-9.1%	-4.1%
EBS AV	-0.056	-0.063	-0.051	0.399	0.395	0.527	-7.7%	-8.6%	-3.1%
GLE FP	-0.047	-0.052	-0.043	0.527	0.416	0.558	-9.4%	-9.7%	-5.0%
GS UN	-0.062	-0.070	-0.054	0.331	0.315	0.430	-7.0%	-8.5%	-2.3%
INGA NA	-0.054	-0.059	-0.047	0.385	0.348	0.520	-9.4%	-9.0%	-3.7%
ISP IM	-0.055	-0.058	-0.049	0.487	0.434	0.578	-9.4%	-10.1%	-4.6%
JPM US	-0.060	-0.068	-0.052	0.368	0.308	0.508	-7.4%	-8.7%	-2.7%
LLOY LN	-0.056	-0.062	-0.051	0.290	0.250	0.314	-7.7%	-7.8%	-2.3%
MS UN	-0.054	-0.060	-0.052	0.284	0.262	0.329	-8.6%	-7.8%	-2.5%
NAB AU	-0.062	-0.074	-0.057	0.415	0.335	0.599	-5.4%	-8.4%	-2.4%
PNC UN	-0.062	-0.068	-0.056	0.365	0.306	0.412	-6.2%	-8.5%	-2.3%
POP SM	-0.058	-0.069	-0.053	0.579	0.527	0.664	-5.8%	-9.1%	-3.4%
RY CT	-0.066	-0.072	-0.059	0.438	0.371	0.553	-4.6%	-8.6%	-2.1%
SAN SM	-0.054	-0.063	-0.051	0.564	0.495	0.665	-6.9%	-9.3%	-4.0%
SLM US	-0.061	-0.067	-0.056	0.164	0.151	0.213	-7.3%	-7.2%	-1.2%
STAN LN	-0.058	-0.066	-0.054	0.555	0.439	0.743	-5.5%	-8.9%	-3.2%
STI UN	-0.061	-0.065	-0.055	0.343	0.239	0.498	-7.2%	-8.6%	-2.4%
STT UN	-0.062	-0.068	-0.056	0.397	0.324	0.410	-7.2%	-9.1%	-2.9%
TD CT	-0.069	-0.075	-0.058	0.377	0.246	0.488	-5.1%	-8.9%	-2.1%
UBSN VX	-0.057	-0.068	-0.050	0.351	0.303	0.393	-7.6%	-8.4%	-2.7%
UCG IM	-0.053	-0.056	-0.047	0.539	0.459	0.580	-7.9%	-9.6%	-4.4%
USB US	-0.064	-0.074	-0.057	0.353	0.325	0.575	-6.5%	-8.7%	-2.3%
WBC AU	-0.061	-0.071	-0.057	0.528	0.480	0.577	-4.9%	-8.7%	-2.8%
WFC UN	-0.065	-0.074	-0.060	0.454	0.370	0.546	-6.3%	-9.4%	-2.9%
					max		-11.3%	-10.1%	-5.7%
					min		-4.5%	-6.7%	-0.1%
					average		-6.9%	-8.7%	-3.0%
					median		-7.1%	-8.7%	-2.7%

SHBA|bank i	α	(conf.int)		β (X^i)	(conf.int)		5% VaR(X^bank i)	5% CoVaR^SHBA|bank i	5% ΔCoVaR^SHBA|bank i
NDA SS	-0.036	-0.041	-0.030	0.495	0.444	0.558	-5.5%	-6.3%	-2.8%
SEBA SS	-0.032	-0.036	-0.030	0.433	0.381	0.499	-6.7%	-6.1%	-3.0%
SHBA SS									
SWEDA SS	-0.036	-0.041	-0.031	0.402	0.353	0.454	-6.9%	-6.4%	-2.8%
8601 JT	-0.046	-0.051	-0.042	0.191	0.122	0.226	-7.1%	-5.9%	-1.3%
8604 JT	-0.045	-0.052	-0.043	0.156	0.123	0.226	-7.8%	-5.7%	-1.2%
ALBK ID	-0.047	-0.055	-0.042	0.004	-0.040	0.004	-11.3%	-4.7%	0.0%
BAC UN	-0.042	-0.050	-0.038	0.220	0.186	0.231	-8.1%	-6.0%	-1.8%
BARC LN	-0.039	-0.044	-0.036	0.242	0.225	0.259	-7.7%	-5.8%	-1.9%
BBT UN	-0.044	-0.055	-0.040	0.244	0.106	0.280	-6.7%	-6.0%	-1.6%
BBVA SM	-0.043	-0.048	-0.040	0.356	0.310	0.387	-7.0%	-6.8%	-2.5%
BK UN	-0.042	-0.050	-0.039	0.294	0.188	0.322	-6.7%	-6.2%	-1.9%
BMO CN	-0.050	-0.054	-0.043	0.258	0.155	0.296	-4.7%	-6.2%	-1.2%
BMPS IM	-0.043	-0.048	-0.039	0.390	0.321	0.438	-7.2%	-7.1%	-2.8%
BNP FP	-0.041	-0.045	-0.037	0.362	0.280	0.457	-7.5%	-6.8%	-2.8%
BNS CT	-0.049	-0.054	-0.044	0.321	0.234	0.361	-4.8%	-6.4%	-1.7%
BTO SM	-0.043	-0.048	-0.038	0.411	0.223	0.438	-5.1%	-6.4%	-2.0%
C US	-0.041	-0.047	-0.038	0.195	0.186	0.218	-8.2%	-5.7%	-1.6%
CBA AU	-0.047	-0.049	-0.042	0.321	0.309	0.369	-4.5%	-6.2%	-1.6%
CBK GR	-0.044	-0.050	-0.039	0.286	0.245	0.312	-8.5%	-6.8%	-2.4%
CM CT	-0.048	-0.055	-0.041	0.328	0.251	0.377	-5.5%	-6.6%	-1.9%
COF UN	-0.046	-0.052	-0.041	0.175	0.134	0.263	-8.0%	-6.0%	-1.4%
CSGN VX	-0.042	-0.045	-0.037	0.285	0.240	0.388	-7.5%	-6.4%	-2.2%
DANSKE DC	-0.042	-0.050	-0.038	0.207	0.160	0.231	-5.8%	-5.4%	-1.2%
DBK GR	-0.040	-0.046	-0.034	0.381	0.298	0.485	-7.1%	-6.7%	-2.7%
EBS AV	-0.043	-0.048	-0.039	0.262	0.215	0.329	-7.7%	-6.3%	-2.1%
GLE FP	-0.039	-0.045	-0.035	0.303	0.229	0.387	-9.4%	-6.7%	-2.9%
GS UN	-0.045	-0.050	-0.041	0.261	0.205	0.303	-7.0%	-6.3%	-1.9%
INGA NA	-0.039	-0.046	-0.034	0.239	0.217	0.332	-9.4%	-6.1%	-2.3%
ISP IM	-0.041	-0.044	-0.037	0.324	0.290	0.398	-9.4%	-7.2%	-3.0%
JPM US	-0.042	-0.050	-0.040	0.327	0.234	0.342	-7.4%	-6.6%	-2.4%
LLOY LN	-0.042	-0.047	-0.035	0.152	0.120	0.209	-7.7%	-5.3%	-1.2%
MS UN	-0.044	-0.049	-0.039	0.201	0.141	0.238	-8.6%	-6.1%	-1.8%
NAB AU	-0.048	-0.052	-0.044	0.321	0.229	0.384	-5.4%	-6.6%	-1.9%
PNC UN	-0.045	-0.052	-0.038	0.222	0.203	0.297	-6.2%	-5.9%	-1.4%
POP SM	-0.042	-0.046	-0.037	0.355	0.281	0.385	-5.8%	-6.3%	-2.1%
RY CT	-0.048	-0.055	-0.043	0.313	0.170	0.380	-4.6%	-6.2%	-1.5%
SAN SM	-0.041	-0.049	-0.036	0.383	0.288	0.455	-6.9%	-6.8%	-2.7%
SLM US	-0.047	-0.053	-0.042	0.105	0.080	0.181	-7.3%	-5.5%	-0.8%
STAN LN	-0.042	-0.050	-0.038	0.414	0.288	0.476	-5.5%	-6.5%	-2.4%
STI UN	-0.049	-0.053	-0.039	0.145	0.125	0.195	-7.2%	-5.9%	-1.0%
STT UN	-0.043	-0.047	-0.037	0.278	0.230	0.343	-7.2%	-6.3%	-2.0%
TD CT	-0.049	-0.055	-0.043	0.272	0.121	0.333	-5.1%	-6.3%	-1.5%
UBSN VX	-0.045	-0.050	-0.039	0.336	0.209	0.374	-7.6%	-7.1%	-2.5%
UCG IM	-0.041	-0.046	-0.037	0.373	0.313	0.421	-7.9%	-7.0%	-3.0%
USB US	-0.047	-0.054	-0.042	0.268	0.232	0.325	-6.5%	-6.4%	-1.8%
WBC AU	-0.049	-0.052	-0.044	0.281	0.252	0.338	-4.9%	-6.2%	-1.5%
WFC UN	-0.046	-0.053	-0.041	0.220	0.184	0.262	-6.3%	-5.9%	-1.4%
					max		-11.3%	-7.2%	-3.0%
					min		-4.5%	-4.7%	0.0%
					average		-7.0%	-6.3%	-1.9%
					median		-7.1%	-6.3%	-1.9%

SWEDA|bank i	α	(conf.int)		β (X^i)	(conf.int)		5% VaR	CoVaR	dCoVaR
NDA SS	-0.053	-0.063	-0.047	0.812	0.758	0.892	-5.5%	-9.8%	-4.6%
SEBA SS	-0.042	-0.049	-0.036	0.700	0.678	0.788	-6.7%	-9.0%	-4.8%
SHBA SS	-0.053	-0.059	-0.045	0.853	0.832	1.034	-4.7%	-9.3%	-4.1%
SWEDA SS									
8601 JT	-0.065	-0.080	-0.056	0.373	0.163	0.459	-7.1%	-9.2%	-2.6%
8604 JT	-0.065	-0.080	-0.056	0.268	0.183	0.362	-7.8%	-8.6%	-2.0%
ALBK ID	-0.069	-0.081	-0.059	0.008	-0.099	0.008	-11.3%	-6.9%	-0.1%
BAC UN	-0.056	-0.067	-0.051	0.414	0.329	0.416	-8.1%	-8.9%	-3.4%
BARC LN	-0.062	-0.072	-0.051	0.400	0.287	0.430	-7.7%	-9.2%	-3.1%
BBT UN	-0.063	-0.079	-0.057	0.262	0.164	0.365	-6.7%	-8.0%	-1.7%
BBVA SM	-0.062	-0.068	-0.056	0.681	0.596	0.716	-7.0%	-11.0%	-4.7%
BK UN	-0.065	-0.077	-0.054	0.308	0.194	0.419	-6.7%	-8.6%	-2.0%
BMO CN	-0.065	-0.074	-0.056	0.319	0.255	0.421	-4.7%	-8.0%	-1.5%
BMPS IM	-0.059	-0.067	-0.053	0.567	0.537	0.627	-7.2%	-9.9%	-4.0%
BNP FP	-0.051	-0.061	-0.048	0.572	0.526	0.605	-7.5%	-9.4%	-4.5%
BNS CT	-0.070	-0.076	-0.060	0.436	0.287	0.482	-4.8%	-9.1%	-2.3%
BTO SM	-0.064	-0.069	-0.058	0.813	0.681	0.883	-5.1%	-10.6%	-4.0%
C US	-0.055	-0.070	-0.050	0.332	0.260	0.365	-8.2%	-8.2%	-2.7%
CBA AU	-0.068	-0.080	-0.055	0.352	0.281	0.656	-4.5%	-8.4%	-1.8%
CBK GR	-0.053	-0.066	-0.046	0.394	0.370	0.449	-8.5%	-8.6%	-3.4%
CM CT	-0.068	-0.082	-0.059	0.450	0.409	0.626	-5.5%	-9.3%	-2.6%
COF UN	-0.057	-0.073	-0.053	0.282	0.225	0.364	-8.0%	-8.0%	-2.3%
CSGN VX	-0.056	-0.074	-0.051	0.429	0.316	0.470	-7.5%	-8.9%	-3.3%
DANSKE DC	-0.061	-0.072	-0.053	0.330	0.308	0.494	-5.8%	-8.0%	-2.0%
DBK GR	-0.051	-0.056	-0.046	0.601	0.506	0.657	-7.1%	-9.3%	-4.3%
EBS AV	-0.052	-0.063	-0.047	0.449	0.364	0.544	-7.7%	-8.7%	-3.5%
GLE FP	-0.048	-0.059	-0.046	0.526	0.511	0.559	-9.4%	-9.8%	-5.0%
GS UN	-0.059	-0.067	-0.054	0.351	0.300	0.525	-7.0%	-8.3%	-2.5%
INGA NA	-0.053	-0.061	-0.050	0.526	0.494	0.540	-9.4%	-10.2%	-5.1%
ISP IM	-0.059	-0.071	-0.054	0.541	0.331	0.670	-9.4%	-11.0%	-5.1%
JPM US	-0.061	-0.075	-0.054	0.382	0.227	0.467	-7.4%	-8.9%	-2.8%
LLOY LN	-0.064	-0.073	-0.053	0.215	0.199	0.228	-7.7%	-8.1%	-1.7%
MS UN	-0.055	-0.064	-0.049	0.373	0.244	0.396	-8.6%	-8.7%	-3.3%
NAB AU	-0.068	-0.082	-0.057	0.443	0.270	0.541	-5.4%	-9.2%	-2.6%
PNC UN	-0.066	-0.078	-0.060	0.370	0.253	0.432	-6.2%	-8.9%	-2.3%
POP SM	-0.059	-0.075	-0.054	0.666	0.528	0.778	-5.8%	-9.8%	-3.9%
RY CT	-0.069	-0.080	-0.059	0.458	0.302	0.598	-4.6%	-9.0%	-2.2%
SAN SM	-0.059	-0.074	-0.050	0.638	0.455	0.695	-6.9%	-10.3%	-4.5%
SLM US	-0.063	-0.075	-0.059	0.218	0.139	0.223	-7.3%	-7.9%	-1.6%
STAN LN	-0.060	-0.074	-0.051	0.453	0.305	0.692	-5.5%	-8.5%	-2.6%
STI UN	-0.061	-0.075	-0.053	0.311	0.227	0.390	-7.2%	-8.3%	-2.2%
STT UN	-0.065	-0.079	-0.057	0.302	0.210	0.383	-7.2%	-8.7%	-2.2%
TD CT	-0.066	-0.077	-0.060	0.396	0.267	0.441	-5.1%	-8.7%	-2.2%
UBSN VX	-0.062	-0.070	-0.052	0.398	0.341	0.461	-7.6%	-9.2%	-3.0%
UCG IM	-0.055	-0.064	-0.048	0.591	0.522	0.675	-7.9%	-10.2%	-4.8%
USB US	-0.064	-0.076	-0.058	0.361	0.294	0.513	-6.5%	-8.7%	-2.4%
WBC AU	-0.066	-0.075	-0.055	0.431	0.304	0.583	-4.9%	-8.7%	-2.3%
WFC UN	-0.070	-0.077	-0.060	0.386	0.270	0.453	-6.3%	-9.5%	-2.5%
					max		-11.3%	-11.0%	-5.1%
					min		-4.5%	-6.9%	-0.1%
					average		-6.9%	-9.0%	-3.0%
					median		-7.1%	-8.9%	-2.6%