A Study of the Systemic Risk in the Japanese Banking System

- An application of the CoVaR method

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Abstract

CoVaR is one of the pioneering systemic risk measures proposed during the financial turmoil of 2008, introduced by Adrian and Brunnermeier (2008). It is based on the familiar risk measurement *Value-at-Risk (VaR)*. In this thesis we apply both the time-invariant and time-varying *CoVaR* model to econometrically quantify the systemic risk in the Japanese banking sector. Specifically we study the systemic risk that individual financial institutions have on the whole Japanese banking system and the systemic linkage among different financial institutions. We use publicly traded daily equity data from the Tokyo Stock Exchange Market (TSE) spanning from 2001-04-02 to 2015-01-31 of the three biggest Japanese bank holding companies: Mitsubishi, Mizuho and Sumitomo. The TOPIX BANKS index is used as a proxy for the banking system of Japan in the thesis. We found Mizuho to be the riskiest bank in isolation as measured by VaR, but in contrast it has the least contribution to the systemic risk of the banking system. Furthermore we found a greater difference between the systemic risk of the banks using 1% quantiles compared to using 5% quantiles. Examining the pair-wise systemic linkages among the three banks, we find the strongest links to be the systemic risk impact that Sumitomo has on Mizuho and Mitsubishi, and the smallest to be the impact Mizuho has on Mitsubishi, suggesting that Sumitomo is a key player in the Japanese banking system.

Keywords: CoVaR; Japan; Systemic risk; Japanese Banking System

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Contents

1. Introduction

The history of systemic risk in finance and banking can be dated a long way back[1]. In the aftermath of a series of financial crises in the Nordic countries, Mexico, Asia and Russia in the 90s, there has certainly been interest among academia and regulators to study the fragility and contagion of the financial system. However, interest in systemic risk has never been as high as after the most recent global financial crisis, which has deepened our understanding of how devastating the spillover effect has become under the trend of financial integration and innovation. Starting with the American subprime mortgage crisis in 2007, several major financial institutions collapsed in the US the year after, and moreover, like an epidemic the failure of these financial institutions infected the entire financial system and even brought severe consequences to the real economy on a global scale with unprecedented speed. The world economy is still greatly struggling to recover from the recent crisis, with Europe still severely affected by the subsequent Euro sovereign debt crisis.

So what is *systemic risk*? It may easily be confused with another well-known risk: *systematic risk*, also known as market risk or undiversifiable risk. This is e.g. the part of the risk of a portfolio that can't be diversified. Systemic risk – that is being studied in this thesis – is a much more complex and multidimensional phenomenon. Generally speaking systemic risk is the risk that a "small" economic crisis or event triggers a chain reaction which propagates negative effects further onto the entire bank and financial system domestically and globally, as exemplified by the recent financial crisis. However the precise definition of systemic risk is still quite ambiguous and this ambiguous definition is in turn probably one of the causes of the relatively slow development of systemic risk research compared to the substantial work on other type of risks, especially prior to the recent crisis. This global financial crisis has impaired the economy of the world as a whole, but just like a coin has two sides, it has surely reignited researchers and regulators' interests in this subject and

[1] For the history of systemic risk see Banerjee (2011).

consequently triggered them to reconsider the interconnectedness and fragility of the financial system and the importance of measuring and monitoring systemic risk.

CoVaR is one of the pioneering systemic risk measures proposed during the financial turmoil of 2008, introduced by Adrian and Brunnermeier (2008). It is based on the familiar risk measurement *Value-at-Risk (VaR)* which has been widely used for a long time by regulators and researchers as a tool to assess the riskiness of a financial institution in isolation. The prefix "*Co*", added by Adrian and Brunnermeier, stands for *conditional, contagion,* or *comovement.* The idea behind *CoVaR* is quite intuitive: it tries to quantify the systemic risk of an institution relative to the financial system, by looking at the *VaR* of the system when a particular institution is in a distress condition, i.e. when the particular institution is at its 1% (or 5% *VaR*) level. Furthermore they introduce $\Delta CoVaR$ to measure the marginal risk contribution that one institution has on the system during times of distress. Adrian and Brunnermeier (2011) show that there is little correlation between the *VaR* of an institution and its risk contribution to system $\Delta CoVaR$, and consequently, solely monitoring an institution's *VaR* is inappropriate for controlling systemic risk. In addition the *CoVaR* method is not limited to gauging the systemic linkage between a financial institution and the financial system. In the same vein it can also be applied to study the spillover effect between two institutions.[2]

Bandt and Hartmann (2000) label the risk of a systemic event occurring within the financial system as horizontal systemic risk, distinguishing it from the risk of systemic events originating in the financial sector affecting the real economy, which they label vertical systemic risk. In this thesis we limit ourselves to the horizontal systemic risk, and apply the *CoVaR* methodology to the study of systemic risk in the Japanese banking sector. We concentrate on the three largest bank-holding companies that are listed on Tokyo Stock Exchange market (TSE), namely: Mitsubishi UFJ Financial Group, Mizuho Financial Group and Sumitomo Mitsui Financial Group, henceforth referred to as Mitsubishi, Mizuho and Sumitomo

[2] For a detailed explanation of the *CoVaR* methodology, see section 3.2.

respectively. There are in total 95 commercial banks listed on stock exchanges around Japan, of which 90 are listed on TSE. The reason that this thesis has been narrowed down to Mitsubishi, Mizuho and Sumitomo is that these three bank holding companies essentially dominate the Japanese banking sector, holding more than half of the total assets of the 90 banks listed on TSE.[3] Additionally they are the only Japanese banks listed on the Globally Systematically Important Banks (G-SIB) list published by the Financial Stability Board (FSB), an organization founded in 2009. (See Table 8 in the appendix.) More specifically, in this thesis we use daily equity data spanning from 2001-04-02 to 2015-01-31 of Mitsubishi, Mizuho and Sumitomo together with other state variables, for the purpose of answering the following four questions:

1) Firstly, how risky are Mitsubishi, Mizuho and Sumitomo in isolation?

2) Second, to what extent do they contribute to the entire systemic risk of the banking sector?

3) Third, what is the systemic linkage among these three mega banks?

4) Finally, do we get the same results at the 1% and 5% level?

Although there is plenty of literature studying different markets using VaR, and quite a few papers using *CoVaR* since the method was first proposed by Adrian and Brunnermeier, very little research on systemic risk has been undertaken on the Japanese banking system.[4] So it is the hope of the author that this thesis may inspire further research on the Japanese market.

A limitation of this thesis is the omission of any data from the Asia financial crisis and the period leading up to it. It would be interesting to compare these two crises, however due to a series of bank bankruptcies and merges, and other recapitalization events in the late 20th century and the beginning of the 21st century,

[3] This was calculated based on publically available data from Datastream.
[4] For literature review on *CoVaR* see section 2.2.

we were unable to find any date early than 2001-04-02 with data available for all three banks on Datastream.

The remainder of the thesis is organized as follows. Section 2 starts with giving a detailed account of the definition of systemic risk and discusses fragility in the financial system. A survey of the existing literature on systemic risk measurements in general and *CoVaR* in particular can be found thereafter. In section 3, a detailed explanation of the methodologies used in this thesis will be illustrated. Section 4 describes the data along with details of the state variables we use. The empirical analysis can be found in section 5. Section 6 concludes.

2. Previous literature

This chapter begins with presenting existing definitions of systemic risk by different academics and organizations. Then we will discuss why systemic risk in the financial system is of particular interest to academics and regulators. A survey of the existing literature on alternative systemic risk measurements and other papers applying the *CoVaR* methodology can be found in section 2.2.

2.1 Systemic risk

As a result of the recent financial meltdown, there has been an unparalleled growth of interest in academia and among regulators to study contagion and fragility in the financial system and the policy making in response to it. In contrast to this consensus, the precise definition of systemic risk is still quite vague as different researchers and organizations define *systemic risk* by looking at different aspects of it. Several existing definitions from different academics and organizations are presented below:

"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 report, p.177)

"…an event having effects on the entire banking, financial, or economic system, rather than just one or a few institutions."(Bartholomew and Whalen (1995), p.4)

"Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy."(Group of Ten (2001), G10 report on consolidation in the financial Sector, p.126)

"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), p371)

"...an economic shock such as market or institutional failure triggers (through a panic or otherwise) either (X) the failure of a chain of markets or institutions or (Y) a chain

of significant losses to financial institutions, resulting in increases in the cost of capital or decreases in its availability, often evidenced by substantial financial-market price volatility." (*Schwarcz (2008), p.204*)

Except for Kaufman and Scott (2003), all stated definitions from various academics and organizations mention financial systems directly in their definition. However systemic risk or spillover effect should not merely be viewed as a financial system specific risk as argued by other researchers. For instance, Hellström (2003, 2007, 2009) views systemic risk from a technological innovation perspective, Bartle and Laperrouza (2009) compare systemic risk in network industries[5] and financial industries and argue the prominence of systemic risk in network industries. Kerste, et al (2015) and Reboredo (2015) discuss systemic risk in the energy sector. Nevertheless, in the areas of economics, the financial system has been observed to seemingly be contagious and more fragile to a systemic event than other sectors of the economy. Bühler and Prokopczuk (2009) applied a copula-based measure to empirically investigate the grade of systemic risk in the banking sector in comparison with 11 other industry sectors in the U.S. using stock market data from 1990 to 2008. They found that the banking sector had higher levels of systemic risk than other sectors, even compared to non-banking financial sectors, especially during times of market downturns.

In the light of Bandt and Hartmann (2000, 2010), there are at least three reasons that can possibly account for the presence of additional vulnerability in the financial system in general and the banking sector in particular. Firstly, the maturity mismatch inherent in the banking business contributes to this vulnerability. A traditional role of banks is to act as an intermediator between depositors and borrowers. Whereas depositors can withdraw on demand, loans banks make to firms cannot be liquidated at a short notice. This mismatch in maturity may result in insufficient capital reserves to absorb the interbank trading and credit losses if a bank run suddenly happens. Secondly, the high interconnectedness among banks and other financial institutions makes banks and other financial institutions more

[5] Such as, gas, electricity, transport, communications and water supply.

likely to be exposed to each other's disturbance. In the event of a crisis, banks and other financial institutions can contaminate through trading with each other via interbank money markets, derivative markets and large-value payment and security settlement systems, and also simply by investing in similar or correlated assets. Information asymmetry lies behind the third reason. The lack of information between borrowers and financial institutions and between depositors and financial institutions can cause an erosion of confidence and thus make the banking system more vulnerable.

2.2 Systemic risk measurements overview

Since the financial crisis of 2008 reignited interest in the area there is now a multitude of approaches to measuring systemic risk. Various researchers have proposed different approaches to systemic risk measures varying with the data used, the econometrical method employed and the research question of the researcher. Since data is a critical and integral part of any research process and in fact data availability itself has also been the target of research on assessing systemic risk recently, with researchers identifying the lack of reliable and readily usable data as a hindrance for effective systemic risk measurements, we begin by exploring different systemic risk measurements from a data collection and usage point of view.

The data used in a systemic risk measure depends on a number of circumstances. The researcher may have access to non-public information, for example when doing the research from the position of a regulator, or when targeting internal use in large institutions. This allows for different models from those based only on public data. One such example is the *network analysis* described in Chan Lau (2009), in which the bilateral exposures between banks are used to construct a network, which is used to study how one bank failure may cause the failure of other banks, which in turn may cause even more failures and so on. However, while they describe and exemplify their methods, they make few empirical claims due to the fact that they were unable to obtain sufficient data or data of sufficient granularity, a problem that a regulator employing the method clearly would be less affected by.

What data is available often varies from country to country and even when data is available it may not be comparable between countries. E.g. balance sheet data is affected by varying accounting practices, making it difficult for researchers to obtain equivalent data points to be used in systemic risk modeling. A detailed exposure of this issue is provided by Cerutti et al (2012), where they propose consistent data from banks be made available, including exposure linkage data used in the above mentioned network analysis.

Another major aspect is the frequency of the data used in measuring systemic risk. Here two major categories can be discerned: methods using low-frequency data and methods using high-frequency data. Risk measures focusing on macro-level data such as inflation, GDP and unemployment naturally falls into the first category. An example is Borio and Drehmann (2009) who use GDP along with equity, credit and real estate property prices as input to *early warning indicators*, meant to signal when the banking system is in distress. The paper evaluates the performance of an earlier method published in Borio and Lowe (2002), using new data from the period preceding the 2008 crisis, concluding it would've had limited success predicting the crisis. High-frequency methods are typically based on daily stock market prices of equity, credit default swaps (CDS) and similar. Huang et al (2009) use both low and high frequency data, including CDS and equity return, to estimate the *Distress Insurance Premium* (DIP) systemic risk measure as the cost of insurance against financial distress, based on the default probabilities of individual banks and forecasted asset return correlations. Segoviano and Goodheart (2009) also use CDS spreads to calculate a number of *Banking Stability Measures* (BSMs) from a multivariate density function estimated from individual bank's probability of distress.

Adrian and Brunnermeier (2011) estimate their CoVaR measure, which falls into the high-frequency methods category, using asset returns and quantile regression. This is the method used in this thesis. They use publicly traded data at weekly frequency of 1226 financial intuitions consisting of commercial banks, security broker-dealers, insurance companies and real estate companies, covering the period of 1986Q1 to 2010Q4. CoVaR is the VaR of the system when a specific bank or institution is in distress, i.e. the VaR of the system when the bank is at its VaR-level. ΔCoVaR is a useful and comparable measure of the contribution to the risk of the system. In their paper, they estimate CoVaR using both time-invariant and time-varying models. The time-invariant CoVaR model, just as the name implies, produces a single estimation of systemic risk for the entire time period. The shortcoming of this unconditional model is that it can't capture the variation of systemic risk throughout time. Thus they further introduce a time-varying CoVaR model in which they regress the asset returns of each institution and the financial system on selected macro state variables using quantile regression. Furthermore they apply panel regression techniques to construct a forward-△CoVaR model projecting △CoVaR directly using lagged accounting data, such as leverage, maturity mismatch, market-to-book ratio, size, equity return volatility and equity market beta, intended be a counter-cyclical measure to capture the slow build-up of systemic risk in a forward looking manner.

Roengpitya and Rungcharoenkitkul (2011) study the Thai financial system using the methods of Adrian and Brunnermeier (2011). Specifically they study the △CoVaR of the equity prices of 6 major Thai banks, based on stock market data stretching from 1996 to 2009, which notably includes the 1997 Asia financial crisis. The state variables used are the prices and volatility of the SET index (Stock Exchange of Thailand index) at different lags. They give a slightly different definition of △CoVaR: the difference between the distress state CoVaR and the unconditioned VaR of the system is used, instead of the difference between the distress state CoVaR and the median state CoVaR used by Adrian and Brunnermeier (2011). They further use the properties of CoVaR to calculate a financial linkage metric, to measure spillover effects.

López-Espinosa et al (2012) use an *asymmetric* CoVaR, differentiating between contracting and growing balance sheets to study 54 international financial institutions. They find strong evidence for asymmetry and that short-term whole-sale funding contributes strongly to systemic risk.

Girardi and Ergün (2013) use a slightly modified CoVaR where the distress event is defined as the institution experiencing losses worse than the VaR, rather than losses exactly at the VaR level. This modification has useful mathematical properties, allowing backtesting of CoVaR using a simple Kupiec test similar to the procedure for VaR. However, the simple estimation method using quantile regression used by Adrian and Brunnermeier is no longer applicable, and instead they use multivariate Gaussian GARCH models.

Another pioneering systemic measure which also use equity returns and has many similarities with *CoVaR* is *Marginal Expected Shortfall (MES)* developed by Acharya et al (2009). They develop an approach whereby banks can be taxed according to the sum of their expected default losses and their expected contribution to a systemic crisis. The latter is equal to the expected amount a bank is undercapitalized in a future systemic event and referred to as Systemic Expected Shortfall (SES), and this can be estimated from MES and leverage. MES in turn is defined in their report as the average return on the 5% worst days of the market. From this definition it is clear that the conditioning is reversed from that used by Adrian and Brunnermeier in CoVaR (analogous to what they refer to as *Exposure-CoVaR*). The ideas in Acharya et al (2009) are further developed by Brownlees and Engle (2012) in their *SRISK index*. They use a bivariate GARCH model to obtain a time series estimation with better predictive power than that of SES. An advantage of SES compared to the method used in this paper is that the measure is additive with respect to the merging and splitting up of economic entities. This stems in part from the inverted conditioning relative to the one employed in this paper.

Finally, for an excellent in-depth overview see Bisias et al (2012), who carefully discuss and categorize 31 systemic risk measures in multiple ways. They also summarize the methods and list data required for input, output and empirical results of the relevant papers. Furthermore they also provide open source implementations of each measure, listing MATLAB header files for each function in their comprehensive report.

3. Methodology

In this section we introduce the quantitative methodologies employed in this thesis. We begin this section by introducing *Quantile Regression (QR)* which we use to estimate *CoVaR* and *∆CoVaR*. Followed by *QR*, we will present the definition of *CoVaR* and *∆CoVaR* in more detail and describe both the time-invariant and time-varying models in section 3.2.2 and 3.2.3. In the last section, we introduce the *Kupiec test* which we use to validate the quality of our *VaR* models.

3.1 Quantile Regression

Quantile Regression (QR) was first proposed by Koenker and Bassett (1978) and it is a statistical and econometrical approach to investigate the relationship between the explanatory variables X and the response variable at different quantiles of a probability distribution. The classical least squares estimator which only examines how the mean of the dependent variable changes according to the mean variation of a set of independent variables, may be very inefficient in linear models with non-Gaussian errors as Koenker and Bassett (1978) argued in their paper. *QR* provides a more comprehensive view of the relationship between the regressors and the response variable, since *QR* can more accurately describe the shape and interval of the relationship, and in particular is able to grasp the special characteristics of the tail of the distribution.[6]

In the field of financial economics, the application of quantile regression can often be found in the modeling of tail events of financial returns, especially Value at Risk (VaR) estimation. For example, Engle and Mangenelli (2004) proposed a conditional autoregressive value at risk model (CAViaR) based on QR in combination with a GARCH model. See also Christoffersen, Hahn, and Inoue (2001), Giacomini, R., and Komunjer, I. (2005), Taylor (2008) and Gaglianone et al. (2011) for further reading.

[6] After the methodology had first been proposed, it was widely applied and developed in various research areas. The interested reader can refer to Yu et al. (2003), who used some simple examples to demonstrate how the methodology can be effectively used in areas such as medicine, survival analysis, environmental modelling, financial economics and the detection of heteroscedasticity.

Whereas solving OLS manually by hand is quite easy, this is not the case for quantile regression. However, with a computer the minimization problems from quantile regression can be solved efficiently using linear programming and the simplex method. Quantile regression is widely available in most popular statistical software packages. As such, we only give a cursory overview of quantile regression. For a comprehensive treatment of the subject see Koenker and Bassett (1978) and Koenker (2005).

To understand quantile regression we start from a simple linear regression model:

$$y_i = \alpha + \beta x_i + \varepsilon_i \text{ ,}$$

where x_i is the independent variable, y_i is the dependent variable and α and β are the parameters and ε_i the error term.

We may find α and β using OLS by solving the following minimization problem:

$$\min_{\alpha,\beta} \sum_{i=1}^{n} (y_i - (\alpha + \beta x_i))^2$$

Now let's first look at a special case of QR – Median Regression. Recall that median is the 50th percentile. The objective function for the median regression is as follow:

$$\min_{\alpha,\beta} \sum_{1}^{n} |y_i - (\alpha + \beta x_i)|$$

Thus, instead of minimizing the sum of the squared residuals we minimize the sum of absolute residuals. The above expression can be reformulated as follows:

$$\min_{\alpha,\beta} \sum_{y_i > \alpha + \beta x_i} \big(y_i - (\alpha + \beta x_i)\big) - \sum_{y_i < \alpha + \beta x_i} \big(y_i - (\alpha + \beta x_i)\big)$$

By adding weights to scale the deviations, corresponding to the quantile q, we arrive at the corresponding objective function for the qth quantile regression:

$$\min_{\alpha,\beta} \sum_{y_i > \alpha + \beta x_i} q\big(y_i - (\alpha + \beta x_i)\big) - \sum_{y_i < \alpha + \beta x_i} (1 - q)\big(y_i - (\alpha + \beta x_i)\big)$$

By adjusting the scale of q, we can study the distribution of the response variable Y given a set of regressors X under different quantile levels. The resulting line can be interpreted as a conditional linear estimation of the q-quantile for Y for a fixed value of X. Koenker (2001)

3.2 *CoVaR*

3.2.1 Definition

CoVaR was first introduced by Adrian and Brunnermeier in 2008. The prefix "*Co*" stands for *conditional, contagion, or comovement*. By taking the nature of systemic risk into consideration, *CoVaR* distinguish itself from other existing risk measures which only look at the risk of an institution in isolation. By quantifying *CoVaR* we can examine the risk that an institution (or the whole financial system) faces when another institution is in its extreme condition. Following Adrian and Brunnermeier (2011), we define such an extreme event to be when the returns of the institution is exactly at value-at-risk level of the institution. The financial system is proxied by a portfolio consisting of all banks, allowing it to be treated just as an institution in the following.

$CoVaR_q^{j|i}$ as presented in Adrian and Brunnermeier (2011) is the q-quantile VaR of an institution j conditional on another institution i being at its q^{th} quantile VaR level, where j often refers to the whole financial system. For ease of reference we will follow the sign convention used in their paper, meaning that we deal with returns rather than losses. As a consequence, VaR is typically a negative value.

This gives us the following (implicit) definition:

$$\Pr\left(X^j \le CoVaR_q^{j|\mathbb{C}(X^i)} | \mathbb{C}(X^i)\right) = q,$$

where X^j is the variable under study of institution j, and $\mathbb{C}(X^i)$ refers to an event relating to variable X^i of institution i.

To measure the marginal risk contribution that one institution has on another institution during times of distress Adrian and Brunnermeier (2011) introduce the risk measure $\Delta CoVaR$. It measures the change in the VaR of institution j as institution i goes from its median state into its distress state (where returns are at VaR-level). Specifically,

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

where Median^i is the 50%-VaR. This measures the risk contribution that institution i has on institution j.

Adrian and Brunnermeier (2011) show that there is little correlation between the VaR^i of an institution and its risk contribution to system $\Delta CoVaR^{\mathrm{system}|i}$.

3.2.2 Time-invariant estimation

As noted, we use Quantile Regression to estimate $CoVaR$, both the time invariant unconditional estimate as well as the conditional version.

Following Adrian and Brunnermeier (2011), we start out with the following linear q-quantile regressions for the time-invariant estimation, one per institution:

$$X^{\mathrm{system}} = \alpha^i + \beta^i X^i + \varepsilon^i$$

where X^{system} is the returns of the system portfolio and X^i the returns of the institution. The estimated parameters then give us an estimation of the qth quantile of X^{system}, conditional on a particular X^i. This is precisely an estimate of the system VaR conditional on X^i:

$$\widehat{VaR_q^{\mathrm{system}}}\big|X^\iota = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i$$

where $\hat{\alpha}_q^i$ and $\hat{\beta}_q^i$ are the estimated parameters from the regression for institution i above. By setting $X^i = VaR_q^i$ we arrive at the $CoVaR$ measure of Adrian and Brunnermeier (2011):

$$\widehat{CoVaR_q^{\mathrm{system}|X^\iota=VaR^\iota}} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i$$

With the corresponding measure for $\Delta CoVaR$ being:

$$\widehat{\Delta CoVaR_q^{\mathrm{system}|\iota}} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i - \left(\hat{\alpha}_q^i + \hat{\beta}_q^i \mathrm{Median}^i\right) = \hat{\beta}_q^i\left(VaR_q^i - \mathrm{Median}^i\right)$$

3.2.3 Time-varying estimation

Since VaR is not directly observable it must be estimated, and a simple way to do this is to find the q-quantile. Adrian and Brunnermeier (2011) expands on this idea to obtain a time-varying estimate by running a quantile regression that regresses the returns of an institution X^i on a number state variables believed to well capture the underlying risk of return.[7] The predicted value of this regression gives a time-varying q-quantile estimate of X^i – i.e. a time-varying estimate of VaR^i. Thus, from the state variables and the regression parameters we calculate a time series of VaR^i.

Specifically, the following regression

$$X_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i$$

leads to the predicted values

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_t$$

Then, for $CoVaR$ we similarly use another regression:

$$X_t^{\text{system}} = \alpha^{\text{system},i} + \beta^{\text{system},i} X_t^i + \gamma^{\text{system},i} M_t + \varepsilon_t^{\text{system},i}$$

Including X^i in the regression will allow us to get the predicted value while conditioning on $X^i = VaR_q^i$, by changing the input to the regression equation (i.e. setting $X^i = VaR_{q,t}^i$). Thus we arrive at the time-varying $CoVaR$ estimate of Adrian and Brunnermeier:

$$CoVaR_{q,t}^i = \hat{\alpha}^{\text{system},i} + \hat{\beta}^{\text{system},i} VaR_{q,t}^i + \gamma^{\text{system},i} M_t$$

From this we can then estimate the time-varying $\Delta CoVaR$ for each institution:

[7] Adrian and Brunnermeier (2011) actually used lagged state variables in their model. Other researchers instead use contemporaneous state variables in estimating CoVaR. In this thesis, we will use contemporaneous state variables, since we found contemporaneous state variables to have more explanatory power than lagged state variables in estimating systemic risk in the Japanese banking system.

$$
\begin{aligned}
\Delta CoVaR_{q,t}^{i} &= CoVaR_{q,t}^{i} - CoVaR_{50\%,t}^{i} \\
&= \hat{\alpha}^{\text{system},i} + \hat{\beta}^{\text{system},i} VaR_{q,t}^{i} + \gamma^{\text{system},i} M_t \\
&\quad - \left(\hat{\alpha}^{\text{system},i} + \hat{\beta}^{\text{system},i} VaR_{50\%,t}^{i} + \gamma^{\text{system},i} M_t\right) \\
&= \hat{\beta}^{\text{system},i}\left(VaR_{q,t}^{i} - VaR_{50\%,t}^{i}\right)
\end{aligned}
$$

Note: $CoVaR$ is based on the same VaR of the system under different conditionings, so it is always calculated at the same quantile (e.g. 1%-VaR). This means that only the quantile of the conditioning event changes between $CoVar_{q,t}^{i}$ and $CoVar_{50\%,t}^{i}$ so that the estimated parameters remain unchanged, whereas $VaR_{q,t}^{i}$ becomes $VaR_{50\%,t}^{i}$.

3.3 Backtesting - Kupiec test

We can see from the above that to some degree $CoVaR$, which studies the dynamics of the spillover effect and co-movement in risk in a system, can be considered an extension of VaR, which in turn measures an institution's risk in isolation. Using time-invariant estimation, we obtain a constant VaR and $CoVaR$ for the whole time period. By contrast, for the time-varying estimation we use a number of state variables to estimate VaR and then to estimate $CoVaR$ based on both the VaR estimation and the state variables. Therefore it is important to backtest the VaR estimation under a time-varying model before we go on with $CoVaR$ and $\triangle CoVaR$ estimation.

There are several backtesting models that can be used to test the accuracy of VaR models. In this thesis we implement the Kupiec frequency test named after Kupiec (1995) which is widely used among researchers and quite intuitive to understand. The basic idea of the Kupiec frequency test is to check if the frequency of violations (by "violation" we mean the case that an actual loss is larger than the corresponding VaR estimation for the day) is consistent with the expected frequency of violations.[8] If these two frequencies significantly deviate from each other under certain predetermined statistical confidence levels, the performance of this VaR model is

[8] Another broadly used test is due to Christoffersen (1996). Christoffersen's test and other Conditional methods, test whether the violations are independent of each other.

poor and should be rejected. The Kupiec frequency test follows a Binomial distribution, thus the probability of having x VaR violations in a sample of N observations is:

$$\Pr(X = x) = \binom{N}{x} q^{x}(1 - q)^{N-x}$$

We can either test if the actual failure frequency is too high by implementing a one-side test or check whether the frequency is too high or too low by doing a two-sided test. In this thesis we will use the two-sided test. In order to do so, we first use the expected violation frequency q (q denotes the q^{th} quantile) to construct a confidence interval $[x_{low}, x_{high}]$ under a certain significance level. (Note: typically a significance level of 1% or 5% is used. Under a two-sided significant test, we thus use 0,05% or 2,5% on each side of the tails.) If the actual number of violations x lies within the confidence interval, the model is accepted, otherwise it is rejected.

4. Data

All data used in this thesis was collected from Datastream. The data consists of daily stock prices from Mitsubishi, Mizuho, Sumitomo and the banking system[9], along with the macro state variables we use for the time-variant *CoVaR* estimation. Furthermore, the daily return of banks and indexes is calculated by $X_t^i = \frac{P_t^i - P_{t-1}^i}{P_{t-1}^i}$ where P_t^i is the price of the bank or the index.

We are using data starting 2001-04-02 and ending 2015-01-31 which covers the recent financial crisis, yet it would have been desirable if we could have included data from before the Asia financial crisis as well. Unfortunately, due to a series of bank bankruptcies and merges, as well as other recapitalization events in the late 20th century and the beginning of the 21st century, we were unable to find any date earlier than 2001-04-02 with data available for all three banks on Datastream. In terms of data frequency, we have in fact attempted to model *CoVaR* with data in both daily and weekly frequency. However, the result suggests that the difference in which data frequency we choose is negligible. In addition we found the results from using daily frequency to be slightly better, and thus we chose this to compute VaR and *CoVaR* in this thesis.

As for the whole banking system, the TOPIX BANK index from TSE is used to represent the banking system of Japan. As an alternative to the TOPIX BANK index, the TOPIX-17 BANK index can also be used as a proxy for the entire banking sector, but its base date only runs back to 2002-12-30. To keep the data length consistent, we settled on the TOPIX BANK index instead.[10]

For the time-variant estimation of $CoVaR_t$ and $\Delta CoVaR_t$, a number of macro state variables are introduced to construct the regression. The state variables should be able to well capture the risk embedded in asset returns from different dimensions. Following the selection criteria suggested by Adrian and Brunnermeier (2011) and

[9] As for the banking system it is explained in further detail below.

[10] According to TSE the constituents are the same and they only differ in their base date and base point. TOPIX-17 Series: Base Date 2002-12-30, Base Point 100; TOPIX Sector Indices: Base Date 1992-01-06, Base Point 1000.

our empirical results, we chose to include the following three state variables in the Time-varying *CoVaR* model:

- ***Nikkei 225 index* daily return** (henceforth referred to as *Nikkei 225*): We use this index as a proxy for daily equity market return. *Nikkei 225* is a price-weighted stock market index for the Tokyo Stock Exchange (TSE). Similar to the Dow Jones Industrial Average, *Nikkei 225* consists of the top 225 blue-chip companies listed on the TSE and the constituents are reviewed annually. Accordingly it is the most widely cited average of Japanese equities.
- ***Volatility index Japan*** (henceforth referred to as *VXJ*): We use the daily data of *VXJ* as a benchmark of future market volatility in the stock market of Japan. *VXJ* is presented by the *VXJ* Research Group at the Center for the Study of Finance and Insurance, and it is considered to be the equivalent to *Chicago Board Options Exchange Market Volatility Index* (known as *VIX*) for the Japanese market.
- ***Yield spread*** (henceforth referred to as *YS*)**:** This variable is calculated by computing the difference between the interest rates of 10-year Japanese government bonds and the 3-month interest rate for government securities and treasury bills. This variable is considered to reflect the time variation in the tails of asset returns. The original raw data of the 10-year Japanese government bond rates obtained from Datastream is listed on a daily basis. However the raw data of the 3-month interest rate we obtained from Datastream is displayed with monthly frequency, so in order to keep the frequency in line with all other data, we converted the data to daily frequency using a constant rate for each month. An alternative would be to use linear interpolation to smooth the data; however when we experimented with this in our model we noticed little to no difference. Looking at the data itself, this finding is hardly surprising, as the monthly variation in both 3-month interest rates for Government securities and treasury bills is very small.

5. Empirical results

The empirical results and analysis thereof can be found in this chapter. There are four sections in this Chapter. Section 5.1 presents descriptive statistics of the data, namely the daily returns of Mitsubishi, Mizuho and Sumitomo, TOPIX BANK as well as the state variables used in the Time-varying *CoVaR* model. The empirical results of the Time-invariant *CoVaR* model will be exhibited and discussed in 5.2, and the time-varying *VaR*, *CoVaR* and *⊿CoVaR* in section 5.3. In addition, since the daily time-varying *VaR* model constructed using the state variables is a crucial first step in estimating the time-varying *CoVaR* and *⊿CoVaR* of the three banks, the *VaR* models of each bank will be backtested using a Kupiec test in this section as well in order to confirm the eligibility of the *VaR* model and provide reliable time-conditional CoVaR estimation. This chapter closes with section 5.4 that explores the systemic linkages of Mitsubishi, Mizuho and Sumitomo.

5.1 Summary statistics

In this section we focus on the statistical properties of the above described data sources. The summary statistics are exhibited below, starting with the statistics for the stock returns of each bank and the system in Table 1, followed by the statistics of the state variables in Table 2. For each time series we show mean, median, standard deviation, minimum, maximum, skewness, kurtosis and the Jarque-Bera test statistic.

For comparison we also include the market index *Nikkei 225*, one of the state variables used in the time-varying modelling, as it is interesting to compare the performance of the three banks and the banking sector index with a market index. There are 3609 samples in each time series. Starting from the top of the table, the daily average return of all three banks clearly outperformed those of the entire banking system as seen in *TOPIX BANK* with a significant marginal. Mitsubishi has the highest daily return of 0,00971% which is 51 times that of *TOPIX BANK*, while Mizuho has the lowest mean of 0,0063% which is in fact still 33 times that of *TOPIX BANK*. However, the market as proxied by *Nikkei 225* has an average daily return higher by an order of magnitude compared with the banking sector and all three banks in our sample.

Table 1

Summary statistics for the daily returns of the three mega banks and the financial system (2001-04-03 to 2015-01-31)

	Mitsubishi	Mizuho	Sumitomo	TOPIX BANK	(Nikkei 225)
Mean	0,00009710	0,00006	0,00007371	0,00001896	0,0002005
Median	0,0000	0,0000	0,0000	0,0000	0,0000
Maximum	0,1576	0,1950	0,1685	0,1524	0,1415
Minimum	-0,1464	-0,1621	-0,1511	-0,1250	-0,1140
Std. Dev.	0,02371	0,02950	0,0268	0,01926	0,01508
Observations	3609	3609	3609	3609	3609
Skewness	0,5150	0,4766	0,3862	0,2533	-0,2614
Kurtosis	7,416	9,057	7,552	7,907	9,941
Jarque-Bera	3091	5653	3205	3659	7285
Probability	0,0000	0,0000	0,0000	0,0000	0,0000

Note: Nikkei 225 included for comparison. Sample period for the stock prices for each bank and the TOPIX Banks and Nikkei 225 indexes start from 2001-04-02, therefore the daily return series starts from 2001-04-03 to 2015-01-31.

We observe that Mizuho accounts for both the largest return (19,5%) and the smallest return (-16,22%) in the sample, which is consistent with its standard deviation of 0,0295 being the largest, i.e. highest price-fluctuation. Notably the standard deviation of the banking sector *TOPIX BANK* is higher than that of the market and all three banks in turn have markedly higher volatility than the banking sector and the market. Since higher volatility often accounts for higher risk, we expect Mizuho to be the most risky entity in isolation, when measuring VaR in later analysis.

Looking at kurtosis we see that all series have values much greater than 3, implying fat tails as is common in financial data. Looking at the Jarque-Beta test statistic further confirms the non-normality of the data. However, this non-normality should not necessarily affect the result of our VaR and *CoVaR* estimations, since quantile regression doesn't assume normality.

Table 2 presents the summary statistics for the macro state variables used in estimating the time-varying *VaR, CoVaR* and *⊿CoVaR* measures. For description and construction of each variable see Section 4.

Table 2

Summary statistics for state variables (2001-04-02 to 2015-01-31)

	Nikkei 225	**VXJ**	**LS**	**YS**
Mean	0,0001992	26,25	0,1207	1,063
Median	0,000	24,86	0,08581	1,098
Maximum	0,1415	91,45	0,5620	1,924
Minimum	-0,1141	11,52	-0,04886	0,2137
Std. Dev.	0,01508	9,493	0,1099	0,3287
Observations	3610	3610	166	3610
Skewness	-0,2612	2,463	1,911	-0,1322
Kurtosis	9,943	12,67	5,940	2,294
Jarque-Bera	7291	17710	160,8	85,42
Probability	0,0000	0,0000	0,0000	0,0000

Note: As mentioned the original data for LS are on a monthly basis; therefore there are only 166 samples in the LS series. However LS is expanded to daily frequency in later analysis. For details on this see Section 4.

In order to look for signs of multicollinearity in our Time-Varying *CoVaR* model, which can lead to overfitting, a correlation matrix table is set up to look for any variables displaying high correlation. Multicollinearity is quite common in econometrical modelling, and although it won't affect the unbiasedness of estimates overall, models that suffer from multicollinearity may display results showcasing a high R^2 but with inefficient estimates, large standard error and Type II errors. Inspection of the correlation matrix below we see that the state variables show very little correlation pairwise; hence we conclude that there is no severe multicollinearity among the state variables.

Table 3

Correlation matrix for state variables

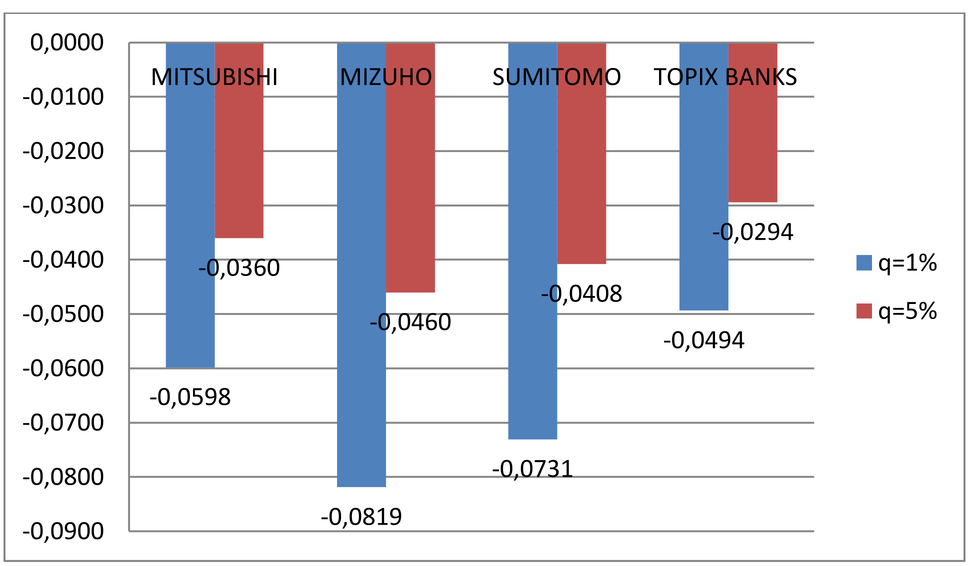
	Nikkei 225	VXJ	YD
Nikkei 225	1,000		
VXJ	-0,0994	1,000	
YD	0,0029	-0,0651	1,000

5.2 Systemic risk analysis: Time-invariant *CoVaR*

In this section the time-invariant measures of systemic risk will be closely examined. Using quantile regression on the three banks and the system, the time-invariant *VaR*, *CoVaR* and *⊿CoVaR* have been calculated at the 1% and 5% level respectively, and displayed below. Based on these measurements we will analyze and rank each bank based on the risk of the bank in isolation as well as the systemic risk it imposes on the system. Observing the results for the different quantiles, i.e. at 1% and 5%, we notice that the rank of each bank in terms of the time-invariant *VaR*, *CoVaR* and *⊿CoVaR* are almost the same. Both results will be presented and discussed in the following figures.

Figure 1

Time-invariant VaR estimation (2001-04-02 to 2015-01-31)



The first observation from the above figure is that Mizuho has the most negative 1%-VaR at -0,08189 as well as the most negative 5%-VaR at -0.0460, implying Mizuho is the riskiest bank among all three banks in isolation, while Mitsubishi has the least negative 1%-VaR at -0,05982 as well as 5%-VaR at -0,0360. Finally the 1%-VaR of Sumitomo is -0,07307, and the 5%-VaR is -0,0408. In other words, the above Time-invariant VaR estimation indicates that the probability is 1% that Mitsubishi, Mizuho and Sumitomo and *TOPIX BANKS* will lose more than 5.98% , 8.19% , 7.31% and 4,94% a day respectively, and the probability is 5% that they will lose more than 3.60% , 4.60% , 4.08% and 2,94% a day respectively.

The next observation is that the VaR of all three banks in isolation all exceed the VaR of the system *TOPIX BANKS* as a whole, which suggests that all three banks are riskier than the whole banking system when measured in isolation. As expected when inspecting the statistical properties of each bank and the banking system in section 4, ranking the banks according to riskiness based on their VaR in this way gives identical results as ranking the banks based on their standard deviation, which is further evidence that standard deviation, although a crude measure, is useful for measuring risk at a glance.

Next the CoVaR corresponding to each bank at both the 1% and 5% quantile is calculated and shown in Figure 2. For the same quantile level, the CoVaR of all banks are approximately the same, suggesting that the distress of either bank leads to similar negative outcomes for the system. The unconditional VaR of the system calculated above is also included in the rightmost column for comparison, since the CoVaR shown in the figure refers to the VaR of the system in different situations, and in particular when a bank is in distress.

Figure 3 exhibit the result of Time-invariant $\triangle$CoVaR. Following Adrian and Brunnermeier (2011), $\triangle$CoVaR in this thesis is calculated as the difference in system VaR between the two events of a specific bank being in distress and operating as usual, i.e. being in its median state (at 50% VaR level). According to our Time-invariant model, Sumitomo is slightly more systemically important than the other

Figure 2

Time-invariant CoVaR estimation (2001-04-02 to 2015-01-31)

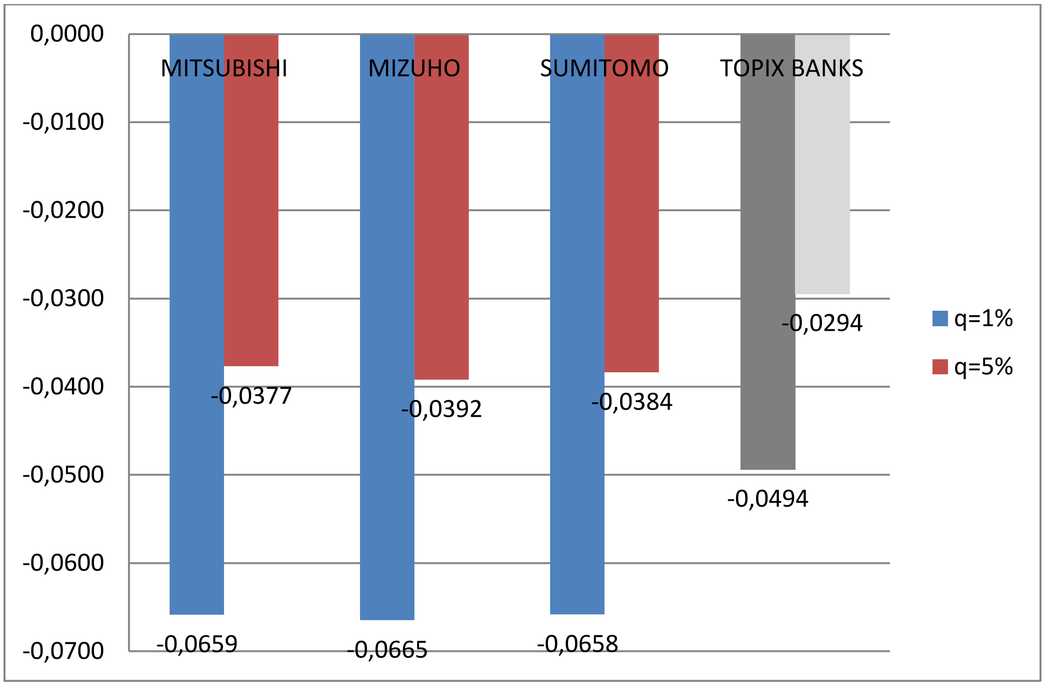
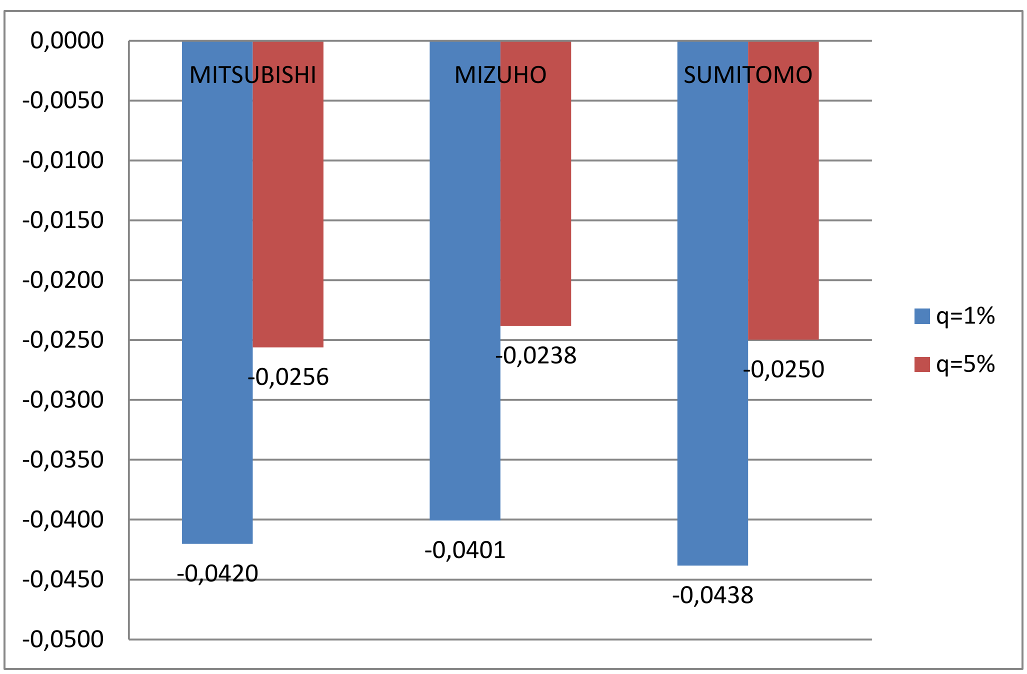


Figure 3

Time-invariant ΔCoVaR estimation (2001-04-02 to 2015-01-31)



two banks when looking at the 1% quantile, whereas Mitsubishi is showing the highest systemic importance at the 5% quantile. However the difference between Mitsubishi's ΔCoVaR and Sumitomo's ΔCoVaR is almost negligible: 0,06% when the quantile is set to be 5% and 0,18% when it is 1%. Therefore to compare the ranking of ΔCoVaR at different quantiles may not be very interesting. What is interesting though is that while Mitsubishi is the least risky bank in isolation as measured by VaR, its distress seems to impart just as much externalities on the whole banking system as the distress of Mizuho or Sumitomo. This again suggests that to regulate and monitor banks solely based on their VaR, i.e. the risk of an institution in isolation, might be insufficient to insulate the banks against systemic risk.

The reason that we adopt the definition of ΔCoVaR from Adrian and Brunnermeier (2011) is that it compares two conditional VaR:s, rather than comparing one conditional VaR with an unconditional VaR. This allows us to better isolate the effect that a single bank being in distress has on the system.

There are other definitions of ΔCoVaR. For instance, Roengpitya and Rungcharoenkitkul (2011) define an institution's ΔCoVaR as the difference between the institution's CoVaR and the system's unconditional VaR, i.e. this is the difference between the rightmost bar and the other bars in Figure 2 above. This may be easier to understand at a glance since the increase in the system's VaR conditioning on different banks can be understood as the risk that the underlying bank has imposed on the banking system. Using their definition to compute ΔCoVaR will indeed give different results from our ΔCoVaR estimation. Furthermore, there is a potential problem in that it is unclear if a conditional VaR can be compared to an unconditional VaR, or if this constitutes comparing apples and oranges. It is outside the scope of this thesis to explore this issue in detail.

5.3 Systemic risk analysis: Time-Varying $CoVaR_t$

In this section the empirical results of the time-varying CoVaR model will be presented and discussed. Unlike the Time-invariant model that yields an estimation that is constant over time, this model is intended to capture the variation of systemic risk over time, allowing us to explicitly study the dynamics of systemic risk under different market conditions.

Similar to the time-invariant model, the first step of estimating $CoVaR_{q,t}^{i}$ and $\Delta CoVaR_{q,t}^{i}$ is to compute $VaR_{q,t}^{i}$. We plot the average conditional VaR_{t}^{i} below at both the 1% and 5% quantile level for Mitsubishi, Mizuho and Sumitomo on a quarterly basis for the entire data period, i.e. from 2001-04-02 to 2015-01-31. In both Figure 4 and Figure 5 a significant drop can be clearly observed in 2008Q4, when the world was in a severe financial crisis. Overall, we see that the VaR_t:s of all three banks follow a similar pattern at both the 1% and 5% level. However, the line showing Mitsubishi's VaR clearly lies above the lines of both Mizuho and Sumitomo, from which we conclude that Mitsubishi is the least risky bank in our data set. While Mizuho and Sumitomo often coincide, we can discern that the downward movements of Mizuho are greater than that of Sumitomo. The results are in line with the VaRs estimated using the time-invariant model in the previous section.

Since computing VaR_{t}^{i} is an indispensable part of modelling time-varying $CoVaR_{t}^{i}$, the quality of our VaR_{t}^{i} results is crucial to all later estimation. Thus we implement a Kupiec Test to backtest and evaluate the reliability of our VaR_{t}^{i}, which is estimated using quantile regression from the selected contemporaneous state variables. We chose to apply a two-sided Kupiec Test thus if the number of violations of each VaR series is between 22-52 and 160-215 for quantiles at 1% and 5% respectively, the model is accepted. As Table 4 shows below, all VaR models at either 1% or 5% quantile level pass the two-sided Kupiec Test which adds credibility to the subsequent $CoVaR_t$ estimation.

Figure 4

1% time-varying VaR

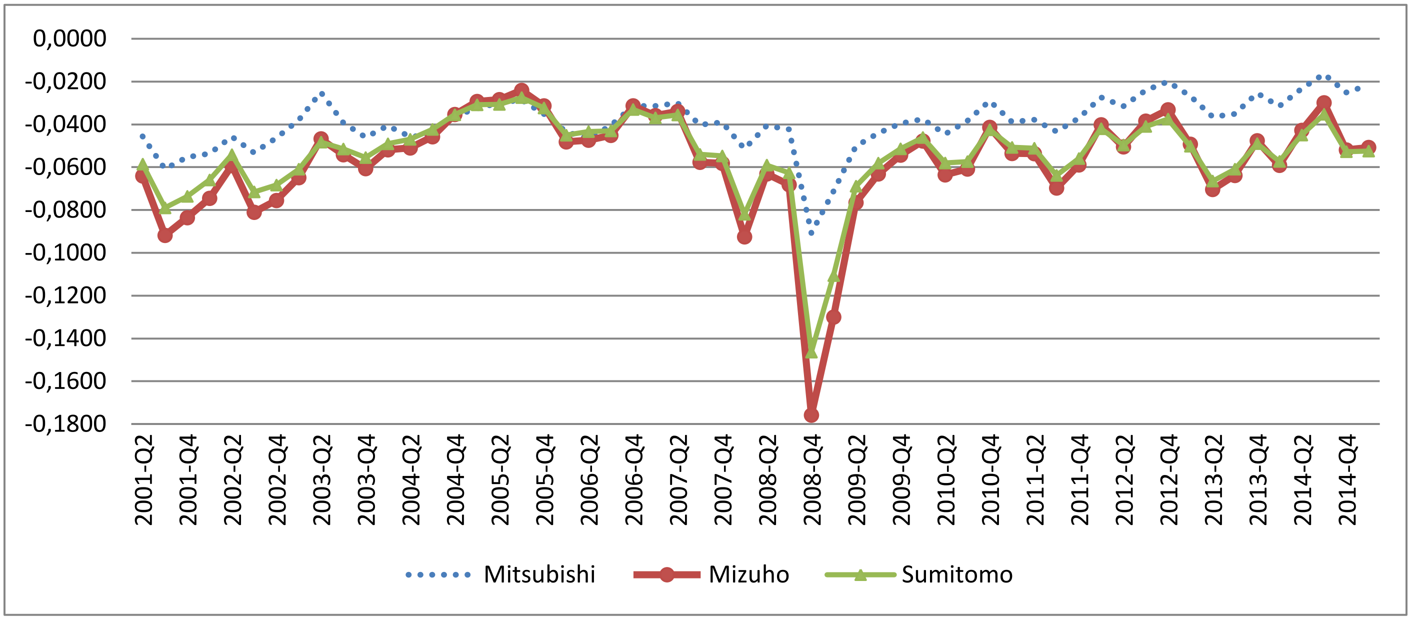


Figure 5

5% time-varying VaR

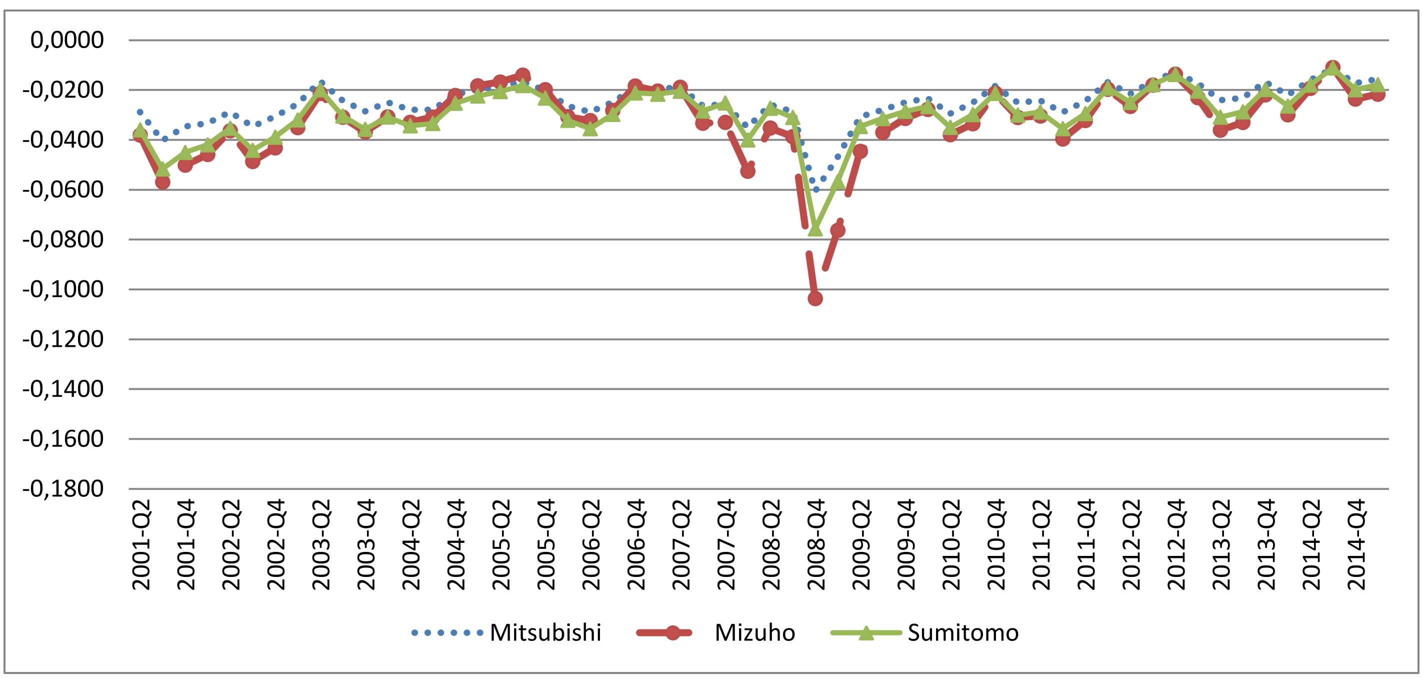


Table 4:

Two-sided Kupiec Test (1% rejection region)

	Mitsubishi	Mizuho	Sumitomo	TOPIX BANKS
1%-Time-varying VaR				
Nr. of violations	38	35	33	35
	Pass	Pass	Pass	Pass
5%-Time-varying VaR				
Nr. of violations	178	179	181	182
	Pass	Pass	Pass	Pass

Note: The acceptance region for 1%-VaR is 22 ~52
The acceptance region for 5%-VaR is 160 ~ 215

Having inspected the credibility of the time-varying VaR models, we can use VaR_t^i together with the selected state variables, namely Nikkei 225, VXJ and Yield Spread[11] to estimate CoVaR_t and ΔCoVaR_t using quantile regression:

$$CoVaR_{q,t}^i = \hat{\alpha}^{\text{system}|i} + \hat{\beta}^{\text{system}|i} VaR_{q,t}^i + \widehat{\gamma 1}^{\text{system}|i} Nikkei\ 225_t + \widehat{\gamma 2}^{\text{system}|i} VXJ_t + \widehat{\gamma 3}^{\text{system}|i} Yield\ Spread_t$$

From this we can then estimate the time-varying $\Delta CoVaR$ for each institution using the following equation:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^i - CoVaR_{50\%,t}^i$$

Inspecting the standard deviation and *Adjusted* R^2 of all three banks at both the 1% and 5% quantile levels in Table 5, all banks have an *Adjusted* R^2 over 60% and almost all chosen state variables are statistically significant at the 1% level, in all models. This in turn suggests that the state variables have strong explanatory power for the time variation in quantiles for CoVaR. Looking at the state variables, we see that high VXJ, high yield spread, low market return and low VaR of each institution tend to be associated with smaller CoVaR_t, i.e. higher systemic risk.

[11] For a detailed explanation of each state variables refer to Section 4.

Table 5:

CoVaR$_t$ Quantile regression results

Panel A: *q=1%*	*α*	*β*	*γ1*	*γ2*	*γ3*	*Adjusted R^2*
Mitsubishi	0,0029	0,4613***	0,5058***	-0,0005***	-0,0071***	68,88%
	(-0,0031)	(0,0207)	(0,4420)	(0,0001)	(0,0019)	
Mizuho	-0,001046	0,2708***	0,6271***	-0,000533**	-0,004895	65,97%
	(0,0071)	(0,0147)	(0,0628)	(0,0002)	(0,0031)	
Sumitomo	-0,001906	0,3933***	0,5685***	-0,00047***	-0,002767	69,67%
	(0,0031)	(0,0137)	(0,0258)	(0,0001)	(0,0018)	

Panel B: *q=5%*	*α*	*β*	*γ1*	*γ2*	*γ3*	*Adjusted R^2*
Mitsubishi	0,0043***	0,5165***	0,4329***	-0,0003***	-0,0055***	67,02%
	(0,0016)	(0,0150)	(0,0222)	(0,0001)	(0,0007)	
Mizuho	-0,0006	0,3596***	0,5249***	-0,0003***	-0,0025***	62,21%
	(0,0016)	(0,0086)	(0,0228)	(0,0001)	(0,0009)	
Sumitomo	0,00111	0,4482***	0,4704***	-0,0003***	-0,0041***	66,18%
	(0,0012)	(0,0147)	(0,0337)	(0,000048)	(0,0007)	

Note : *** denotes statistical significance at the 0.01 level; ** statistical significance at the 0.05 level and * statistical significance at the 0.10 level.

Table 6:

Average Time-varying estimation

	Mitsubishi	**Mizuho**	**Sumitomo**	**Rank**		
1%				***1***	***2***	***3***
VaR	-0,0392	-0,0575	-0,0542	Mizuho	Sumitomo	Mitsubishi
CoVaR	-0,0349	-0,0359	-0,0384	Sumitomo	Mizuho	Mitsubishi
ΔCoVaR	-0,0180	-0,0155	-0,0213	Sumitomo	Mitsubishi	Mizuho
5%				***1***	***2***	***3***
VaR	-0,0252	-0,0326	-0,0299	Mizuho	Sumitomo	Mitsubishi
CoVaR	-0,0230	-0,0235	-0,0239	Sumitomo	Mizuho	Mitsubishi
ΔCoVaR	-0,0129	-0,0116	-0,0134	Sumitomo	Mitsubishi	Mizuho

The average of the time-varying CoVaR and △CoVaR results for the three banks are exhibited in Table 6 above (the corresponding time-invariant estimates can be seen in Table 9). We rank each banks according to their VaR, CoVaR and △CoVaR estimates. The 1% and 5% quantile rankings give identical ranking. From Table 6 we can thus conclude that Mizuho is the riskiest and Mitsubishi is the least risky bank in isolation, whereas Sumitomo is observed to have the largest marginal systemic risk effect measured by △CoVaR on TOPIX BANKS, i.e. on the whole banking system. However Mizuho which has the highest VaR unexpectedly has the lowest △CoVaR measured in absolute value.

In order to better understand how each bank systemically impacts the Japanese banking sector over time, we plot the average conditional $\Delta CoVaR_t^i$ at both the 1% and 5% quantile level for Mitsubishi, Mizuho and Sumitomo on a quarterly basis from 2001-04-02 to 2015-01-31. Studying Figure 6 and Figure 7, a significant drop can again clearly be observed in 2008Q4 when the Japanese banks also were seriously affected by the global financial meltdown. In addition to this, just like in Figure 4 and Figure 5 all three banks follow a very similar pattern over time, suggesting that they affect the Japanese banking system in the same fashion during a crisis. Aside from the above observations, we found two other interesting facts by comparing Figure 6 and Figure 7. We start by looking at the 5% quantile case, where all three banks follow each other closely. The line of Mizuho is slightly higher than that of the others, meaning that its systemic importance is somewhat lower, and the other two lines almost entirely coincide. During the financial crisis the △CoVaR of all three banks increase substantially in magnitude, with near-identical increase. In the 1% case we again see that all three banks follow a common trend, but this time with a larger gap. Mizuho is again above the others, and more consistently so, whereas Sumitomo now clearly is below the other two, especially during the most critical time of the financial crisis in 2008Q4. Clearly the gap between the banks is much greater than during calmer time periods. Thus it seems like the volatility in systemic risk as measured by △CoVaR greatly increases during times of extreme financial distress. From this we conclude that even though the probability of an event such as the 2008 financial crisis may be very small the effects should it still happen are particularly dire. This further highlights the importance of a deeper understanding of systemic risk and the need for further study thereof.

Figure 6:

Quarterly average time-varying 1%-ΔCoVaR

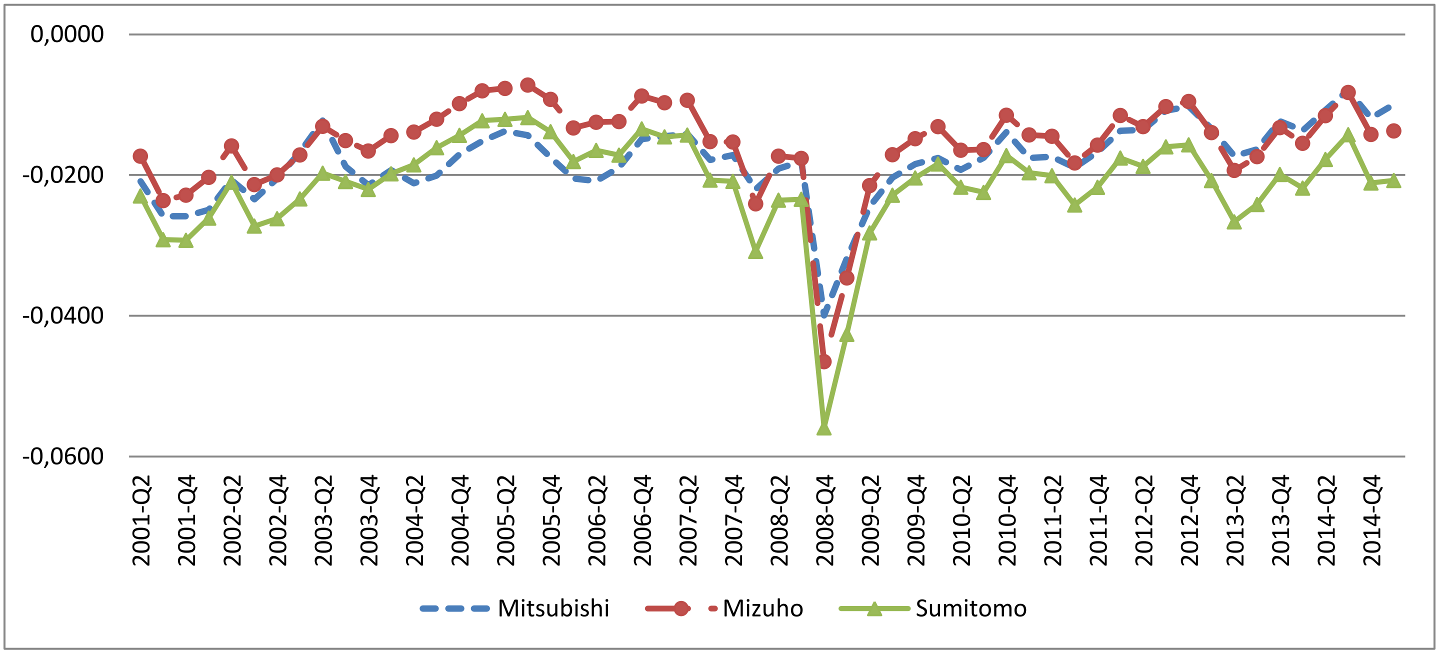
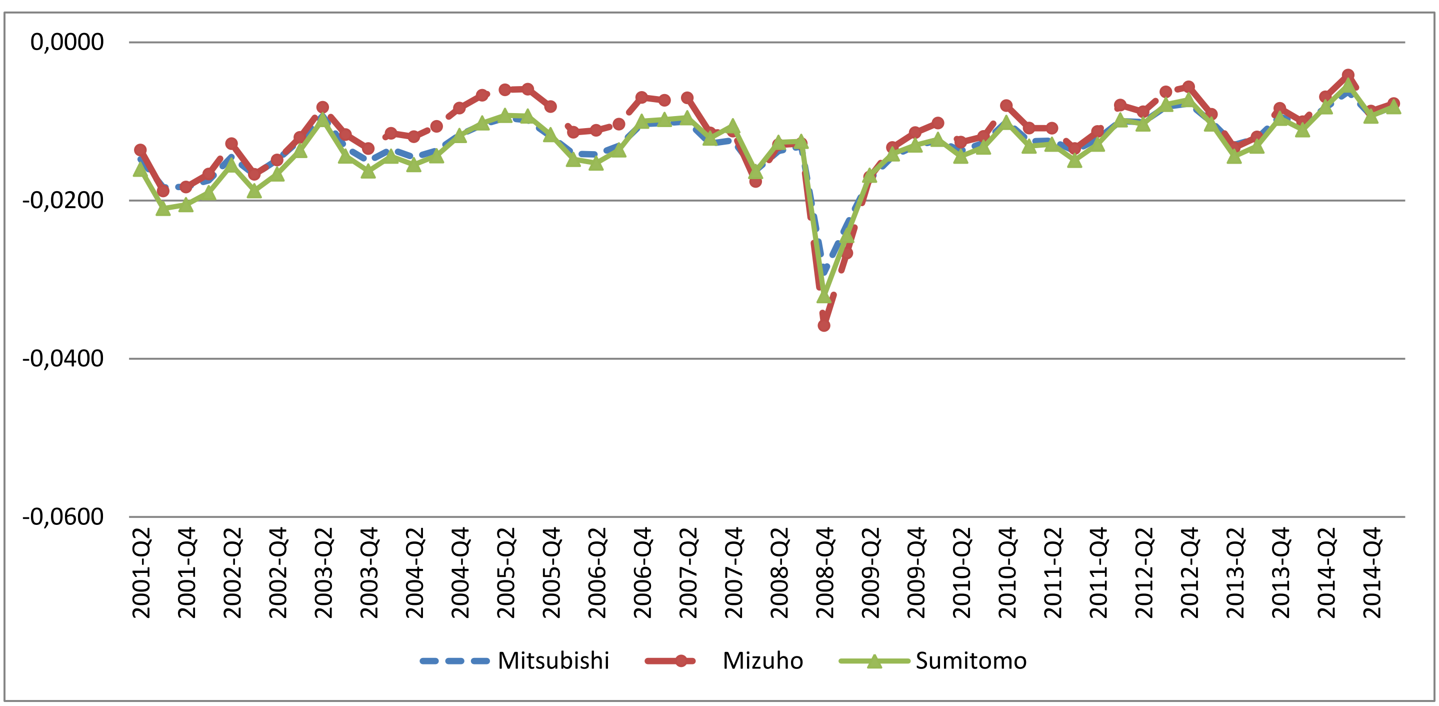


Figure 7:

Quarterly average time-varying 5%-ΔCoVaR



5.4 Linkage

In the previous section we studied the effect an individual bank had on the financial system, and in this section we study the effect a bank has on other banks, in a pair-wise comparison.

We can obtain a measure for the impact one bank being in distress has on the risk of another bank by specifying the VaR in the definition of CoVaR given by Adrian and Brunnermeier (2011) to be the VaR of another bank, rather than the VaR of the system as we have previously assumed. Similar to Roengpitya and Rungcharoenkitkul (2011) we use the time-varying measure of ΔCoVaR_t to calculate the linkage between banks. Finally, we present time average results of all measures.

We used essentially the same procedure as for estimating the time varying $CoVaR_t^{\text{system}|i}$ measure, replacing *system* with *k* to obtain $CoVaR_t^{k|i}$, where *k* refers to the bank affected instead of the system, and *i* refers to the bank whose distress affects *k*, i.e. *i* is the bank that is conditioned upon.

Thus the second regression for estimating CoVaR becomes:

$$X_t^k = \alpha^{k,i} + \beta^{k,i} X_t^i + \gamma^{k,i} M_t + \varepsilon_t^{k,i}$$

Consequently (see previous section and section 3.2.3) we estimate $CoVaR_t^{k|i}$ and $\Delta CoVaR_t^{k,i}$ at quantile q using:

$$CoVaR_{q,t}^{k|i} = \hat{\alpha}^{k|i} + \hat{\beta}^{k|i} VaR_{q,t}^i + \widehat{\gamma 1}^{k|i} Nikkei\ 225_t + \widehat{\gamma 2}^{k|i} VXJ_t + \widehat{\gamma 3}^{k|i} Yield\ Spread_t$$

$$\Delta CoVaR_{q,t}^{k|i} = CoVaR_{q,t}^{k|i} - CoVaR_{50\%,t}^{k|i}$$

$\Delta CoVaR^{k|i}$ allows us to compare the effect different banks being in distress has on a single bank, i.e. we can compare different values of $\Delta CoVaR^{k|i}$ by changing i. However, we if we change k these values are no longer comparable.

In Table 7 the averages of the estimated $\Delta CoVaR_t^{k|i}$ for all banks k and i pairwise can be found[12]. Looking column by column we see that the distress of Sumitomo has the largest effect on risk for both Mitsubishi and Mizuho, whereas Sumitomo is most affected by the distress of Mizuho, and this holds both at the 1% and 5% level. Comparing the result of $\Delta CoVaR^{k|i}$ to that of $CoVaR^{k|i}$ we see that Sumitomo again has the largest effect on Mizuho and Mitsubishi, at both the 1% and 5% level; i.e. the results are mostly the same. However, looking at how Sumitomo is affected by the other banks we see that $CoVaR^{k|i}$ is almost identical when any of the two banks is in distress. $\Delta CoVaR^{k|i}$ is however different, and thus comparing with the median state seems to provide additional information.

Table 7: Average of estimated $\Delta CoVaR_t^{k|i}$ for all banks k and i pairwise.

Linkage	1% $\Delta CoVaR^{k\|i}$		
i \ k	Mitsubishi	Mizuho	Sumitomo
Mitsubishi	N/A	-0,0242	-0,0271
Mizuho	-0,0155	N/A	**-0,0300**
Sumitomo	**-0,0258**	**-0,0418**	N/A

Linkage	5% $\Delta CoVaR^{k\|i}$		
i \ k	Mitsubishi	Mizuho	Sumitomo
Mitsubishi	N/A	-0,0171	-0,0164
Mizuho	-0,0105	N/A	**-0,0177**
Sumitomo	**-0,0143**	**-0,0222**	N/A

Linkage	1% $CoVaR^{k\|i}$		
i \ k	Mitsubishi	Mizuho	Sumitomo
Mitsubishi	N/A	-0,0782	**-0,0701**
Mizuho	-0,0496	N/A	**-0,0699**
Sumitomo	**-0,0562**	**-0,0867**	N/A

Linkage	5% $CoVaR^{k\|i}$		
i \ k	Mitsubishi	Mizuho	Sumitomo
Mitsubishi	N/A	-0,0436	-0,0383
Mizuho	-0,0319	N/A	**-0,0387**
Sumitomo	**-0,0334**	**-0,0462**	N/A

In order to make $\Delta CoVaR^{k|i}$ comparable for different values of k, we scale these values by the time average size of the unconditional VaR (of k), converting them into percentages:

$$\frac{\Delta CoVaR_{q,t}^{k|i}}{VaR_q^k}$$

where $VaR_q^k = \frac{1}{n}\sum_t VaR_{q,t}^k$ with n data points.

[12] See Figure 10 to Figure 12 in the Appendix for pairwise $\Delta CoVaR_t^{k|i}$ over time.

This allows us to compare the impact one bank being in distress has on banks of different sizes.

Figure 8 and Figure 9 show the average $\Delta CoVaR_{q,t}^{k|i}$ scaled by VaR_q^k along with the rank. We see that the largest effect observed is that of how Sumitomo being in distress affects Mizuho, where we see an increase in VaR from the median state to the distress state equivalent to 68,23% and 72,69% of the unconditional VaR of Mizuho at the 1% and 5% level respectively. Similarly the smallest effect seen is that of how Mizuho being in distress affects Mitsubishi, where we see an increase equivalent to 41,58% and 39,44% of the unconditional VaR of Mitsubishi and Mizuho at the 1% and 5% level respectively. We see that the ranking of largest and smallest is the same at both the 1% and 5% level, and overall the ranking is similar at both levels, with the only exception being that #2 and #3 are reversed.

Comparing the 1% and 5% level results, we see that the differences between the effects the banks have on each other are more pronounced in the 1% case. We see that both Mizuho and Mitsubishi are strongly linked to Sumitomo, but these two banks are not as strongly linked to each other: the effects of either Mizuho or Mitsubishi being in distress on Sumitomo are larger than the effects the banks have on each other, both in the 1% and 5% case. Finally, the effect of Sumitomo being in its 1% distress state has the overall largest effects of the studied events.

Figure 8:

Average 5% $\Delta CoVaR^{k}_{5\%}$ scaled by $VaR^{k}_{5\%}$.

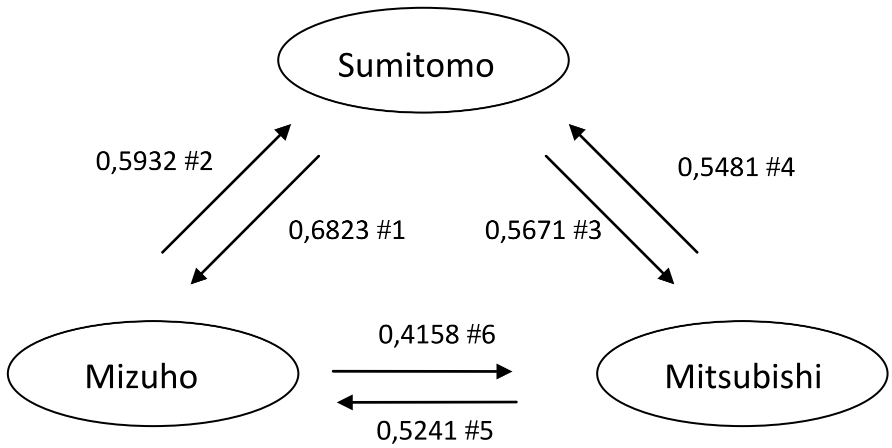
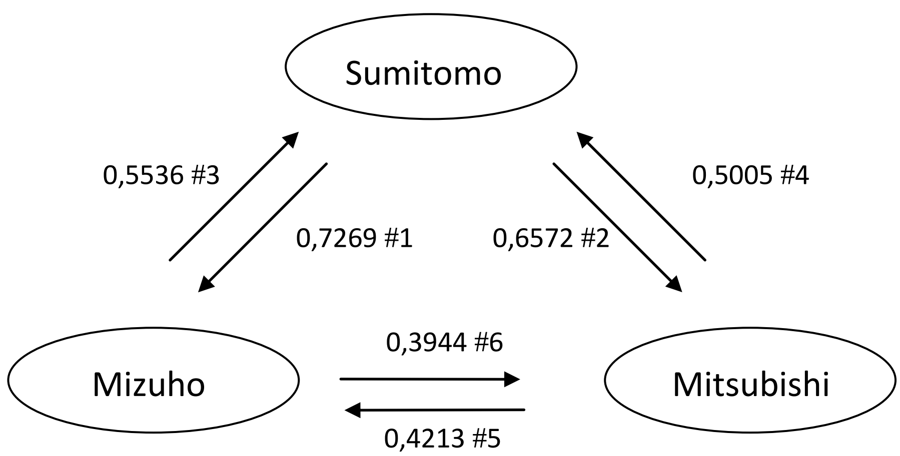


Figure 9:

Average 1% $\Delta CoVaR^{k}_{1\%}$ scaled by $VaR^{k}_{1\%}$.



6. Conclusion

In this thesis we set out to analyze systemic risk in the Japanese banking system. In particular we have studied the systemic risk of the three Japanese mega banks dominating the Japanese banking system: Mitsubishi, Mizuho and Sumitomo.

We have studied

1) how risky the banks are in isolation, by measuring the VaR of the banks,
2) the contribution of the banks to the systemic risk of the banking sector, by measuring the $\Delta CoVaR$ between each bank and the system (as proxied by TOPIX BANKS),
3) the systemic linkage among the banks, by measuring the $\Delta CoVaR$ between each bank, pair-wise, and
4) how using a 1% and 5% significance level affects the result.

We found Mizuho to be the riskiest bank in isolation, followed by Sumitomo and then Mitsubishi. In contrast, we see that Sumitomo seems to be the bank that has the largest contribution to the systemic risk of the banking system.

This is also in line with the result we get in the linkage study, where Sumitomo is the bank whose distress has the largest effect on other banks. It has both the overall strongest linkage and also the strongest effect on each of the other two banks. Sumitomo not only is the bank whose distress has the strongest effect on the other two banks, it is itself also most affected by the distress of either of the other two banks, whereas the linkage between Mitsubishi and Mizuho is the weakest (in both directions).

From this we conclude that Sumitomo seems to be a key player of the Japanese banking system, either by having a direct causal effect on the other banks, or as an entity whose distress can serve as a warning signal.

In order to verify the validity of our models we performed the well-known Kupiec test on our VaR measures, all of which passed. We note that the adjusted pseudo-R^2 values are all high, suggesting our models have decent explanatory power.

Furthermore we found that using 1% quantiles rather than 5% quantiles gave a more pronounced difference between the banks for all measured risk measures, suggesting that the spillover effect is more pronounced for more extreme events. Thus it would seem that if one has enough data available, it is more fruitful to study the data using a more extreme quantile.

Future areas of improvement on the work in this thesis:

- We could use other types of data, such as financial statement data of banks. In this thesis our estimates are all based on high frequency stock market prices and their volatility. Financial statements could conceivably complement this with low frequency high quality data.
- We could take mergers and other changes of financial entities into account. This is especially important for longer time periods, and could enable us to use data that includes the interesting time period leading up to the 1997 Asia financial crisis.
- It is beyond the scope of this thesis, yet it would have been desirable to develop a backtesting model to verify the credibility of our CoVaR models directly, similar to the Kupiec test we carried out for our time varying VaR models in this thesis. This may require using other modelling techniques than used in this paper. It would be an interesting extension to the work in this thesis to repeat the work with the CoVaR definition given by Girardi and Ergün (2013) which does allow for a Kupiec test. This however also requires the use of a less straightforward estimation technique compared to the intuitive method using Quantile Regression employed in this thesis.

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Appendix

Table 8: G-SIBs as of November 2014

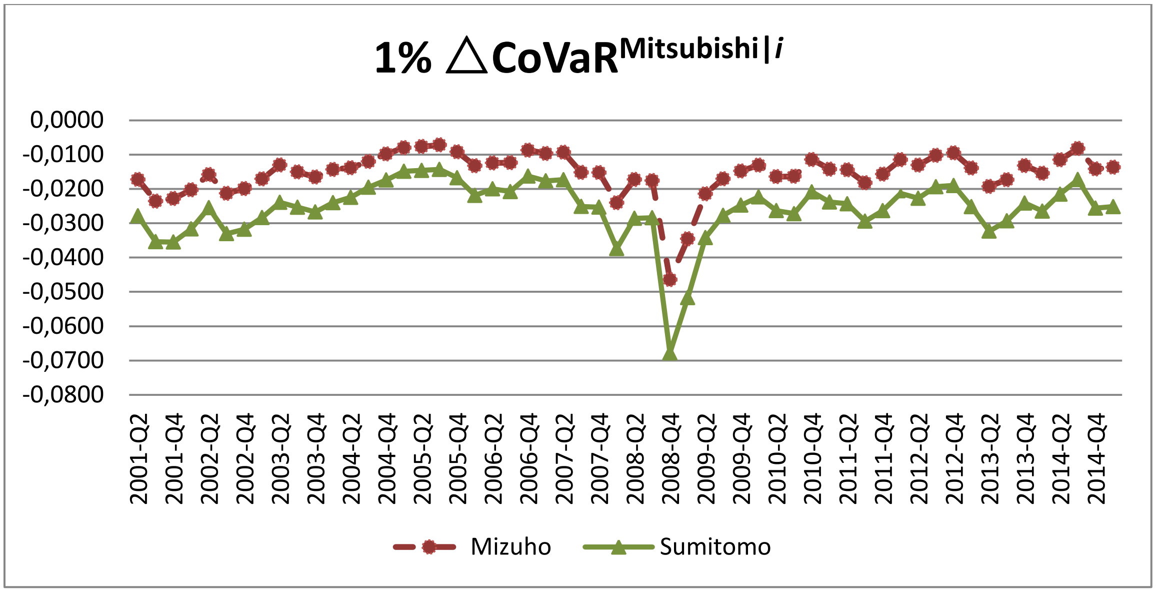
Americas		Asia		Europe	
JP Morgan Chase	USA			Groupe BCPE	United Kingdom
Citigroup	USA			HSBC	United Kingdom
Bank of America	USA	Agricultural Bank of China	China	Royal Bank of Scotland	United Kingdom
Goldman Sachs	USA	Bank of China	China	Barclays	United Kingdom
Morgan Stanley	USA	Industrial and Commercial Bank of China Limited	China	Standard Chartered	United Kingdom
Bank of New York Mellon	USA	***Mizuho FG***	***Japan***	BNP Paribas	France
BBVA Compass	USA	***Sumitomo Mitsui FG***	***Japan***	Société Générale	France
State Street	USA	***Mitsubishi UFJ FG***	***Japan***	Group Crédit Agricole	France
Wells Fargo	USA			Credit Suisse	Switzerland
				UBS	Switzerland
				Deutsche Bank	Germany
				Unicredit Group	Italy
				ING Bank	Netherlands
				Santander	Spain
				Nordea	Sweden

Data Source: http://www.bis.org/bcbs/gsib/gsibs_as_of_2014.htm

Table 9: Time-invariant CoVaR results

	Mitsubishi	Mizuho	Sumitomo	Rank		
1%				***1***	***2***	***3***
VaR	-0,0598	-0,0819	-0,0731	Mizuho	Sumitomo	Mitsubishi
CoVaR	-0,0659	-0,0665	-0,0658	Mizuho	Mitsubishi	Sumitomo
ΔCoVaR	-0,0420	-0,0401	-0,0438	Sumitomo	Mitsubishi	Mizuho
5%				***1***	***2***	***3***
VaR	-0,0360	-0,0460	-0,0408	Mizuho	Sumitomo	Mitsubishi
CoVaR	-0,0377	-0,0392	-0,0384	Mizuho	Sumitomo	Mitsubishi
ΔCoVaR	-0,0256	-0,0238	-0,0250	Mitsubishi	Sumitomo	Mizuho

Figure 10: △CoVaR of Mitsubishi when other banks in distress



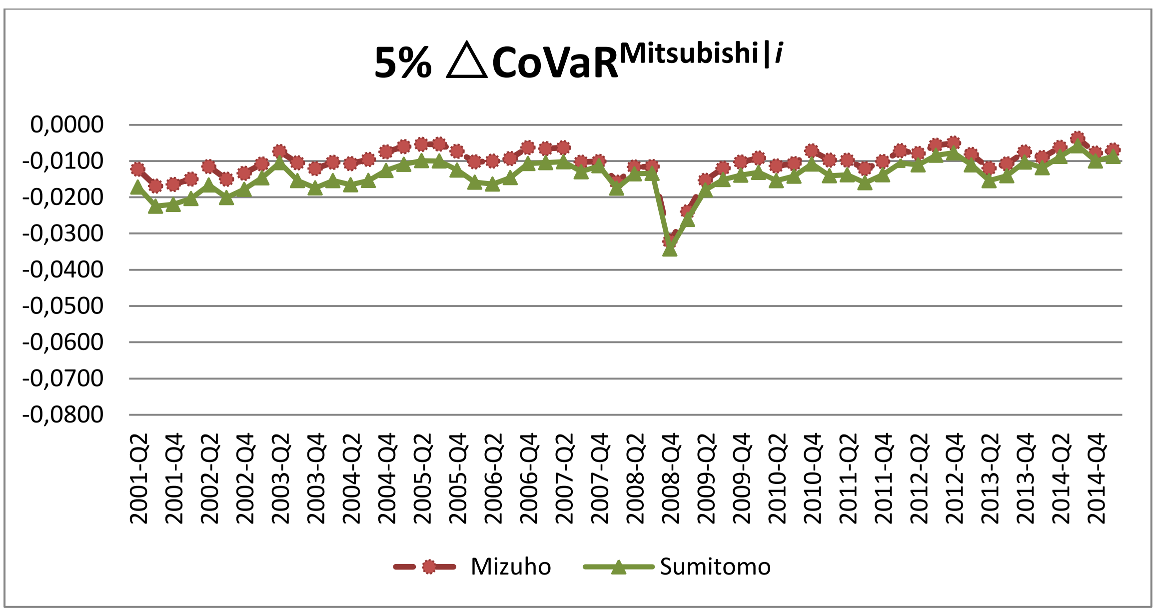
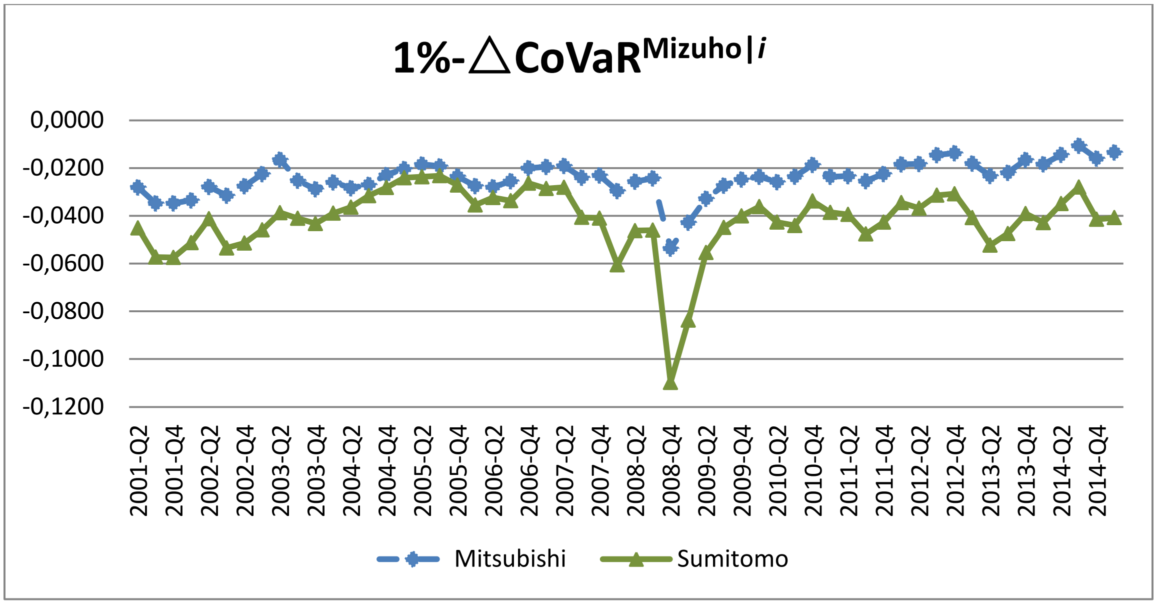


Figure 11: △CoVaR of Mizuho when other banks in distress



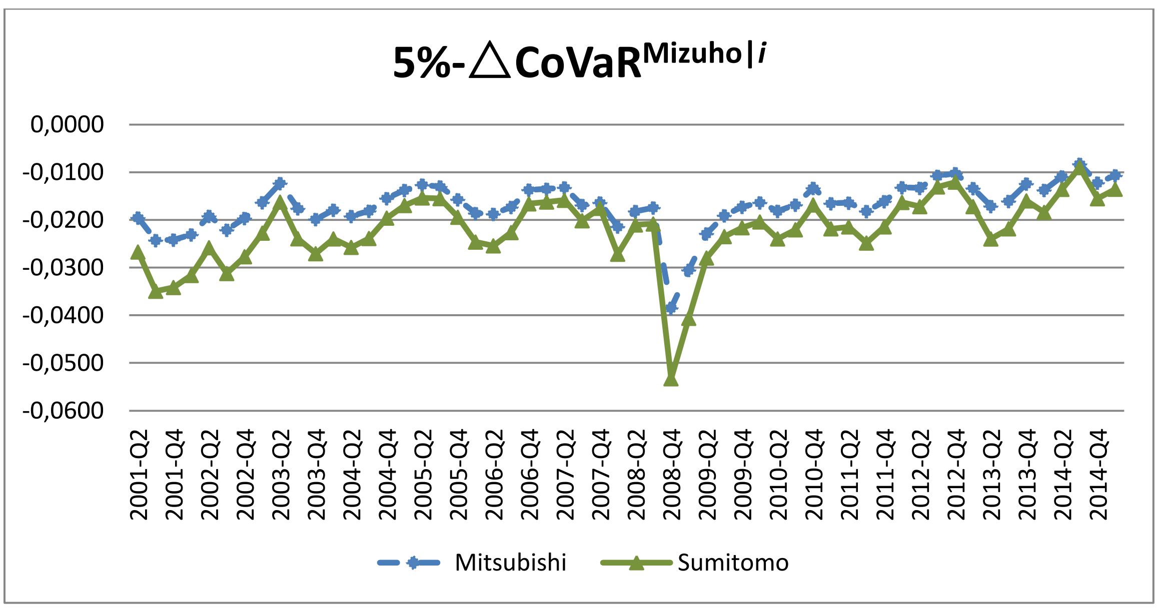


Figure 12: △CoVaR of Sumitomo when other banks in distress