ISCTE Business School
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MEASURING SYSTEMIC RISK IN THE SOUTHEAST ASIAN BANKING SYSTEM: A COVAR APPROACH

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Abstract

The recent financial crisis has proven how integrated are the economies and the financial markets, and therefore how important is to understand the spillover effects, as well as to measure and manage systemic risk. The Southeast Asian market is no exception, even though little research has been done on systemic risk and contagion in this region. Thus, this dissertation analyzes the cross-sectional dimension of systemic risk in the Southeast Asian banking system, applying Adrian's and Brunnermeier's *CoVaR* methodology to the six major Southeast Asian banks. The results of this dissertation evidence that, over the period between 4th of November 2015 and 1st of November 2019, the banking institutions indeed contribute to the systemic risk of the Southeast Asian financial market; all the banks are sensitive to a systemic crisis; and in fact there are interconnections across them.

JEL classification: C22, G21, G32

Keywords: Systemic Risk, CoVaR, Quantile Regression, Southeast Asia

Resumo

A recente crise financeira veio evidenciar o quão integrados estão as economias e os mercados financeiros, e consequentemente o quão importante é entender os efeitos colaterais, assim como medir e gerir o risco sistémico. O mercado financeiro do Sudeste Asiático não é exceção à integração, no entanto existem poucos estudos acerca do risco sistémico e de contágio nesta região. Assim sendo, esta dissertação pretende analisar a dimensão transversal do risco sistémico no mercado bancário do Sudeste Asiático, aplicando a metodologia de Adrian e Brunnermeier, intitulada de *CoVaR*, aos seis maiores bancos do Sudeste Asiático. Para o período entre 4 de novembro de 2015 e 1 de novembro de 2019, os resultados apontam que de facto os bancos selecionados contribuem para o risco sistémico da região; que todos os bancos seriam afetados por uma crise financeira no Sudeste Asiático; e que existem interligações entre os bancos.

Classificação JEL: C22, G21, G32

Palavras-chave: Risco Sistémico, CoVaR, Regressão de Quantis, Sudeste Asiático

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List of Abbreviations

AR – Autoregressive

BBCA.JK – Bank Central Asia

BBRI.JK – Bank Rakyat Indonesia

BSI – Banking Stability Index

CDS – Credit Default Swap

CoVaR – Conditional Value at Risk

D05.SI – DBS Group Holdings

DiDe – Distress Dependence Matrix

ECB – European Central Bank

EVT – Extreme Value Theory

EWMA – Exponential Weighted Moving Average

FTASEANAS – FTSE ASEAN All Share Index

GARCH – Generalized Autoregressive Conditional Heteroskedasticity

JPoD – Joint Probability of Distress

MES – Marginal Expected Shortfall

MLE – Maximum Likelihood Estimation

O39.SI – Oversea-Chinese Banking

OLS – Ordinary Least Squares

PAO – Probability that at Least One Bank becomes Distressed

PUBM.KL – Public Bank BHD

SES – Systemic Expected Shortfall

SII – Systemic Impact Index

SRISK – Systemic Risk indices

U11.SI – United Overseas Bank

VaR – Value at Risk

VI – Vulnerability Index

1. Introduction

The increasing globalization phenomenon has been contributing for the rapid integration of economies and financial markets (Lehar, 2005; Shahzad, Arreola-Hernandez, Bekiros, Shahbaz and Kayani, 2018). The markets and institutions are now more interdependent, and the co-movements associated with that may result in widespread contagion and further simultaneous failure (Lehar, 2005; Petrella, Laporta and Merlo, 2018). Therefore, it is essential to understand the spillover effects across the financial system, and to measure and manage it, especially during times of financial distress (Giesecke and Kim, 2011; Shahzad et al., 2018).

The recent financial crisis of 2007-2009 is an evidence of how losses tend to spread across financial institutions, threatening the financial system as a whole (Adrian & Brunnermeier, 2016). The Value at Risk (*VaR*), considered as the most commonly used risk measure, is unable to capture tail interdependence relationships, as it does not consider the institution as part of a system, but in isolation (Girardi and Ergün, 2013; Petrella et al., 2018). As a result, the systemic risk (i.e. the risk that an initial disturbance spreads across the whole financial system, affecting adversely the real economy) is now subject of regular discussion and several alternative risk measures, which do not suffer from *VaR*'s limitations, have been proposed in the literature (Girardi and Tolga Ergün, 2013; Gottesman and Leibrock, 2017).

Perhaps the most common alternative risk measure is Conditional Value at Risk (*CoVaR*), firstly proposed by Tobias Adrian and Markus K. Brunnermeier in 2008. The *CoVaR* refers to the *VaR* of the financial system conditional on the distress of a financial institution. Likewise, Adrian and Brunnermeier developed a measure of an institution's contribution to systemic risk, Delta Conditional Value at Risk ($\Delta CoVaR$), defined as the financial system's or financial institution j's increase in *VaR* when an institution i is under distress, which they consider to be their main systemic risk measure.

This dissertation contributes to measure and analyze the cross-sectional level of systemic risk in the Southeast Asian banking system, applying Adrian's and Brunnermeier's (2008) *CoVaR* methodology. In particular (i) to identify which banks contribute the most for the systemic risk of the Southeast Asian financial market; (ii) to determine which banks are more at risk if a financial crisis occurs in the Southeast Asia; (iii) and to evaluate and capture financial linkages and interconnectedness between the banks. Indeed, the Southeast Asia reveals a strong economic growth and global integration, which makes more relevant the study of common exposures and interconnections.

The data included in this research are the daily adjusted closing prices of the banking institutions included in the top 10 constituents of the FTSE/ASEAN 40 Index, on the 31st of October 2019, and the FTSE ASEAN All-Share Index, for the period from the 31st of October 2014 to the 31st October 2019. The six banking institutions meeting the requirements are: DBS Group Holdings (D05.SI), Oversea-Chinese Banking (O39.SI) and United Overseas Bank (U11.SI), from Singapore; Public Bank BHD (PUBM.KL), from Malaysia; and Bank Central Asia (BBCA.JK) and Bank Rakyat Indonesia (BBRI.JK), from Indonesia.

From the empirical application of this dissertation we draw the following three main conclusions: for the period from 4th of November 2015 to 1st of November 2019, (i) the United Overseas Bank and the Oversea-Chinese Banking are the banking institutions contributing the most for the systemic risk of Southeast Asian financial market; (ii) if a crisis does occur in the Southeast Asian financial market, the Indonesian banking institutions are the institutions more at risk; and lastly (iii) that there are financial linkages across the six banking institutions, but mostly within banking institutions from the same country of origin.

The remainder of the dissertation is structured as follows. The section 2 introduces the theoretical background and literature related to systemic risk and *CoVaR*. The section 3 explains Adrian's and Brunnermeier's (2016) methodology to estimate *CoVaR* and $\Delta CoVaR$ via quantile regression. The section 4 describes the empirical application, and the presentation and analysis of the estimation results. Lastly, in section 5, the main conclusions are highlighted and suggestions for further researches are made.

2. Literature Review

This section introduces the theoretical background and literature related to (2.1) systemic risk, and (2.2) Conditional Value at Risk. It constitutes the basis for further understanding of the chosen methodology and empirical application in section 3 and 4, respectively.

2.1. Literature on Systemic Risk

The literature on systemic risk is broadly defined and began to appear before the recent financial crisis of 2007-2009, making significant progresses in analysing systemic risk, in particular contagion risks (ECB, 2009; Georg, 2011). Even so, this event emphasized the importance of studying such severe financial instabilities, resulting in a growing literature on systemic risk definition and measurement after that (Bandt and Hartmann, 2000; Smaga, 2014). Consequently, the concept of systemic risk, frequently understood as the probability of causing cascades of default, is now associated not only with contagion, but also with macroeconomic shocks and pro-cyclical behaviour (Georg, 2011). Important to realize that there is no consensus on the definition of systemic risk, which therefore implied the development of numerous systemic risk measures.

In this subsection, the literature on systemic risk definition is provided, the nature and dimensions of the concept are developed, and the main systemic risk measures, excepting the Conditional Value at Risk, are presented.

2.1.1. The Concept of Systemic Risk

Even though the literature on systemic risk definitions is extensive (see the definitions proposed by Bandt and Hartmann (2012), ECB (2009), Trichet (2009), Schwarcz (2008)), generally speaking systemic risk implies the transmission of an initial disturbance which affects one or more financial institutions (e.g. an economic shock or institutional failure), through a contagion mechanism across the interconnected elements of the financial system, which spreads, most likely indirectly, negative effects to the real economy (Martínez-Jaramillo, Pérez, Embriz and Dey, 2010; Smaga, 2014).

2.1.2. The Different Dimensions of Systemic Risk

The initial disturbance might be endogenous, i.e. arises from the default of a group of financial institutions (e.g. several smaller institutions that are *systemic as a herd*) or derived from a systemically important financial institution (e.g. an *individually systemic* institution so interconnected and large that can cause negative risk spillover effects on others), or exogenous when its source is outside the financial system, i.e. when it arises from an initial external shock (e.g. imbalances in the real economy) (Georg, 2011; Kaufman and Scott, 2003; Smaga, 2014). Simultaneously, Smaga (2014) also classifies the initial shock as macro or micro, depending on whether it arises when the financial system becomes exposed to aggregate risk (e.g. sudden increase in the inflation rate), or when the failure of an individual institution impacts negatively the financial system (e.g. failure of a systemically important financial institution), respectively. Similarly, ECB (2009) and Bandt and Hartmann (2012) distinguish between idiosyncratic and systematic shocks. Bandt and Hartmann (2000) associate the idiosyncratic shock to a sequential propagation of the shock causing contagion from one financial institution or market to the other, and the systematic shock to a simultaneous destabilization effect, impacting the financial institutions and markets at the same time.

The literature commonly accounts for two systemic risk dimensions, a time (also known as cyclical, time-varying, time series) dimension and a cross sectional (also known as structural) dimension (Bisias, Flood, Lo and Valavanis, 2012; Borio, 2010; Pederzoli and Torricelli, 2017; Smaga, 2014). The time dimension refers to the evolution of aggregate risk in the financial system along time, and the cross-sectional dimension implies the allocation of systemic risk within the financial system at a particular time (Bisias et al., 2012; Borio, 2010; Freixas et al., 2015). In other words, in the time dimension, financial institutions endogenously take excessive risk when volatility is low, and in the cross-sectional dimension, spillovers amplify initial adverse shocks (Adrian and Brunnermeier, 2016).

Additionally, Bandt & Hartmann (2012) and ECB (2009) make a distinction between a horizontal and vertical perspective of systemic risk. On the one hand, the horizontal view focus on the financial system alone, i.e. what makes instability widespread within the financial system, on the other, the vertical view relies on the interaction between the financial system and the economy at large, i.e. what makes instability widespread within the financial system and the real economy (ECB, 2009; Hartmann, Bandt and Peydró, 2015). Nevertheless, in practice this distinction between systemic risk affecting only the financial system and systemic risk affecting the real economy is difficult to establish (Smaga, 2014).

Provided the different distinctions of the initial shock – idiosyncratic or systematic, exogenous or endogenous, and sequential or simultaneous – and the different dimension of systemic risk, one might conclude about the complexity of this phenomenon (ECB, 2009). For this reason and in order to reduce the dimensions of systemic risk, ECB (2009) suggests limiting attention to three main forms of systemic risk: the contagion risk, the risk of macro shocks, and the risk of the unravelling of imbalances.

2.1.3. The three main forms of systemic risk

According to the literature, the transmission of financial instability can achieve systemic dimensions when driven by contagion, macro shocks, or/and unravelling imbalances. Indeed, it is essential to understand all the elements of the financial system that can lead to them (Trichet, 2009).

Contagion relates to the way the failure of one financial institution spillovers to other financial institutions, i.e. an idiosyncratic shock that becomes more widespread in the cross-sectional dimension, often in a sequential fashion (Bédard, 2012; ECB, 2009; Trichet, 2009). Bandt and Hartmann (2012) and Bédard (2012) recognize two main contagion channels in the banking system: the exposure channel (also known as counterparty contagion) and the informational channel (also known as informational contagion, information asymmetry or reassessment failures). On the one hand, the authors associate the exposure channel to the potential for "domino effect" through direct exposures in interbank markets and payment system, or common exposures to similar non-bank assets. On the other, the authors relate the informational channel to contagious depositor withdrawals or other funding problems when creditors are imperfectly informed about the type of shocks hitting banks (idiosyncratic or systematic) and about their physical exposure (asymmetric information). The authors also reinforce that the channels can work in conjunction but also independently. In contrast, some literature considers informational spillovers separately from contagion, associating contagion only with direct channels, and informational spillovers with indirect channels (Georg, 2011; Smaga, 2014).

Macro shocks (also known as common shock) refer to a widespread exogenous shock adversely affecting numerous intermediaries and/or markets in a simultaneous fashion (e.g. interest rate increases, stock market crashes, or exchange rate devaluations) (Bandt & Hartmann, 2000; ECB, 2009; Trichet, 2009). According to Bandt & Hartmann (2012), the reason why banks are affected simultaneously in those events, independently of their preparation, might be related with news about a cyclical downturn (e.g. depositors may avoid offering loans to banks).

Lastly, the risk of unravelling of imbalances refers to the endogenous accumulation of widespread imbalances in the financial system over time, which then unravels, affecting negatively several intermediaries and/or markets in a simultaneous fashion. Trichet, (2009) identified the unravelling of imbalances as driven by herd behaviour in investment, leverage to finance investments exposures and complex and opaque financial contracts. The risk of macro shocks and the risk of unravelling of imbalances are particularly relevant for the pro-cyclicality of financial systems, although contagion can also play a role in it (ECB, 2009).

According to ECB (2009), these three mechanisms are not mutually exclusive and may materialise independent, but generally in conjunction with each other. Freixas et al. (2005) reinforce this idea defending that all of them materialise to some degree and reinforce each other. For instance, an adverse macroeconomic shock and the unravelling of financial imbalances might contribute to bank contagion, once banks weakened by an widespread shock are more vulnerable to contagion (Bandt and Hartmann, 2000; ECB, 2009; Trichet, 2009).

2.1.4. The Different Measures of Systemic Risk

Given the complex and adaptive nature of the financial system, it is not realistic to expect a single systemic risk measure, and probably not even desirable (Bisias et al., 2012; Borio, 2011). Indeed, there exist different approaches emphasizing different dimensions and elements of systemic risk, and each has its own properties and limitations (Bisias et al., 2012; Gualandri and Noera, 2014). Even though the literature reflects a significant progress regarding the technical knowledge and capability for preventing systemic shocks, for instance a single systemic risk measure or framework collecting the plurality of the several individual measures, would be desirable for monitoring and managing financial stability (Bisias et al., 2012; Gualandri and Noera, 2014). This dissertation emphasizes the work done by Acharya et al. (2016), Billio et al. (2012), Brownlees and Engle (2012), Goodhart and Segoviano (2009), Huang et al. (2009), and Zhou (2010). Adrian's and Brunnermeier's (2008) *CoVaR* is only presented in the next subsection (2.2). In addition, for a more complete survey regarding systemic risk measures, see Bisias et al. (2012).

Amongst several alternative systemic risk measures proposed in the literature, Acharya et al. (2016) focus on the cross-sectional Systemic Expected Shortfall (*SES*) to measure each financial institution's contribution to systemic risk, considering the Marginal Expected Shortfall (*MES*) and leverage as predictors. Brownlees & Engle (2012) introduce *SRISK* Index as a measure of an institution's contribution to systemic risk, and function of the degree of leverage, size and a time-varying measure of *MES*. Billio et al. (2012) suggest several systemic risk measures using principal components analysis and Granger-causality networks, in order to estimate common factors and to identify statistically significant linkages among the institutions, respectively. Huang et al. (2009) propose a systemic risk measure based on the price of insurance against the financial distress, using Credit Default Swaps (*CDS*) spreads and asset return correlations. Goodhart & Segoviano Basurto (2009) also employ *CDS* data to propose the Joint Probability of Distress (*JPoD*) and the Banking Stability Index (*BSI*) to analyse common distress across the banks; the Distress Dependence Matrix (*DiDe*) to estimate pairwise conditional probabilities of distress; and the Probability that at Least One Bank becomes Distressed (*PAO*), to assess the distress in the system associated with a specific bank. Lastly, Zhou (2010) adopts Extreme Value Theory (*EVT*) framework to estimate Segoviano's and Goodhart's (2009) *PAO*, and two new measures, the Systemic Impact Index (*SII*), which measures the size of the systemic impact if one bank fails, and the Vulnerability Index (*VI*), which measures the impact on a particular bank when other part of the system is in distress.

2.2. Literature on Conditional Value at Risk (*CoVaR*)

The most commonly used systemic risk measure in the literature is Adrian's and Brunnermeier's (2008) Conditional Value at Risk (*CoVaR*) (Dičpinigaitienė & Novickytė, 2018). Likewise, it is the methodology applied through the empirical application of this study in section 4.

In this subsection, *CoVaR* and $\Delta CoVaR$ are defined, *Exposure-CoVaR* and *Network-CoVaR* are presented, and the main literature on systemic risk measurement inspired by *CoVaR* and where *CoVaR* methodology is strictly applied is provided.

2.2.1. The Definition of *CoVaR* and Δ*CoVaR*

The *CoVaR* of an institution relative to the system is defined as the *VaR* of the whole financial system conditional on the institution being in a particular state (Adrian and Brunnermeier, 2016), i.e., it is the percentage loss of the financial system or financial institution *j* that will not be exceeded, when the financial institution *i* is under distress. Concerning $\Delta CoVaR$, Adrian and Brunnermeier (2008) define it as the difference between the *CoVaR* conditional on the distress of an institution and the *CoVaR* conditional on the median state of that institution. In other words, $\Delta CoVaR$ is the financial system's or financial institution *j*'s increase in Value at Risk when the institution *i* is in distress, therefore measuring the systemic risk contribution of financial institutions.

Taking into account the several systemic risk dimensions and forms presented in the previous sub-section (2.1), it is possible to conclude that *CoVaR* is a cross-sectional horizontal systemic risk measure, able to capture macro shocks (or common shocks) and contagion effects (through direct and indirect spillovers). Nonetheless, in order to capture the unravelling of imbalances, Adrian and Brunnermeier (2008) also purpose the *forward*-$\Delta CoVaR$, which will not be addressed in this dissertation.

2.2.2. *CoVaR, Exposure-CoVaR* and *Network-CoVaR*

Adrian and Brunnermeier (2016) clarify that $\Delta CoVaR^{j|i}$ is directional – i.e. $\Delta CoVaR^{system|i}$ of the system conditional on institution *i* is not necessarily equal to $\Delta CoVaR^{i|system}$ of the institution *i* conditional on the system being in distress – and the superscripts *j* and *i* can stand for individual institutions or for a set of institutions. With this in mind, the authors appoint for three possible directions for $\Delta CoVaR$, a "regular" $\Delta CoVaR$, an *Exposure-CoVaR* and a *Network-CoVaR* (Adrian & Brunnermeier, 2016). The "regular" $\Delta CoVaR$ stands for the $\Delta CoVaR^{system|i}$, i.e. the financial system's increase in Value at Risk, when the institution *i* is in distress; the *Exposure-CoVaR* refers to $\Delta CoVaR^{j|system}$, i.e. the institution *j*'s increase in Value at Risk in the event of a financial crisis; and the *Network*-$\Delta CoVaR$ refers to $\Delta CoVaR^{j|i}$ whenever *j* and *i* stand for individual institutions, i.e. the institution *j*'s increase in Value at Risk, when the institution *i* is in distress (Adrian and Brunnermeier, 2016).

These nomenclatures will be used through the empirical application in the section 4, as they provide relevant information about the interconnections across the financial institutions and between the financial institutions and the system. For instance, the Δ*CoVaR* allows us to conclude which institutions are riskier for the system, the *Exposure-CoVaR* inform about the institutions that are more at risk in the case of a system-wide distress, and the *Network-*Δ*CoVaR* allows the creation of tail-dependency's network across all the financial institutions (Adrian and Brunnermeier, 2016).

2.2.3. Systemic Risk Measures Inspired by *CoVaR*

Adrian and Brunnermeier (2008)'s methodology has been the base for a number of studies on systemic risk measurement, where authors slightly modify the original *CoVaR*, suggesting some adjustments, extensions and different estimation approaches. Hong (2012) introduces an analytical form of *CoVaR*. Huang and Uryasev (2018) propose *CoCVaR* – the *CoVaR* of the financial systemic conditional on the distress of an institution – and Δ*CoCVaR* – the difference between the *CoCVaR* of an institution under distress and the *CoCVaR* in the median state of the same institution –, which measures the contribution of an institution to the systemic risk. Bernal, Gnabo and Guilmin (2014) include the Kolmogorov-Smirnov test based on bootstrapping, developed by Abadie (2002), in order to determine whether the contribution is significant to the systemic risk. While Adrian and Brunnermeier (2016) estimate *CoVaR* using quantile regressions, Girardi and Ergün (2013) use a multivariate GARCH and modify the *CoVaR*, by changing the definition of financial distress from an institution being exactly at its *VaR* to being at most of its *VaR*. Likewise, Reboredo and Ugolini (2014) characterize *CoVaR* using copulas, firstly by computing the cumulative probability for the *CoVaR* from a copula function, and then inverting the marginal distribution function for this cumulative probability to obtain the *CoVaR*.

2.2.4. Researches Applying a *CoVaR* Approach

Similarly, some studies rely exactly on the Δ*CoVaR* methodology to measure the systemic risk across different sectors, fields and countries. Borri, Di Giorgio, Caccavaio and Sorrentino (2013) analyse the systemic risk contribution of Italian listed banks for the period from 2000 to 2011. Drakos and Kouretas (2015) examine the contribution of foreign banks to the systemic risk in the United States and the contribution of subsegments of the financial system to the systemic risk in the United Kingdom from 2000 to 2012. Gauthier, Lehar and Souissi (2010) analyse the contribution of each bank to the systemic risk of the Canadian banking system. López-Espinosa, Moreno, Rubia and Valderrama (2012) identify the main determinants behind systemic risk in international large-scale complex banks using *CoVaR*. Muharam and Erwin (2017) estimate the contribution of each bank to the systemic risk of the banking sector in Indonesia for the period of 2005 to 2014. Petrella et al. (2018) assess the contribution of each European country to the systemic risk of the European stock market from 2008 to 2017. Roengpitya and Rungcharoenkitkul (2010) quantify the level of systemic risk and financial linkages in the Thai banking sector from 1996 to 2009 employing panel data. Wong and Fong (2010) analyse the interconnectivity among eleven Asian-Pacific economies from 2004 to 2009.

3. Methodology

Following the approach presented by Adrian and Brunnermeier (2008), this section presents the quantitative methodologies employed in this dissertation. We begin by defining *CoVaR* and Δ*CoVaR* in detail (3.1). Thereafter, we formally define *VaR* and describe the volatility adjusted historical method for *VaR* estimation (3.2), applied in the *CoVaR* and Δ*CoVaR* estimation. In the last subsection, we present quantile regression and explain its approach in estimating *CoVaR* and Δ*CoVaR* (3.3).

3.1. *CoVaR* and Δ*CoVaR*

Even though *VaR* is probably the most commonly used risk measure by financial institutions, it fails to capture systemic risk, since it does not consider the institution as part of the system, but in isolation. As a result, and especially since the most recent financial crisis, there is a growing literature on systemic risk and interconnectedness across the financial system. *CoVaR* was one of the several systemic risk measures proposed by the literature and has inspired several others. Likewise, we apply Adrian's and Brunnermeier's (2008) methodology through this dissertation.

CoVaR is formally defined as the *q*% quantile of the conditional probability distribution, i.e.,

$$\Pr\left(X^i \middle| C\left(X^i\right) \leq -CoVaR_q^{j|\left(X^i\right)}\right) = q\%, \qquad (1)$$

where, $CoVaR_q^{j|(X^i)}$ is the *VaR* of institution *j* or the financial system, conditional on some event $C\left(X^i\right)$. The event $C\left(X^i\right)$ is commonly the distress of the financial institution *i*, that is, the institution *i*'s loss being at or above its $(100 - \alpha)$ confidence VaR_q^i.

The financial institution *i*'s contribution to the systemic risk of the financial institution *j* or the financial system is measured by Δ*CoVaR*, which is denoted by,

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50}^i}, \qquad (2)$$

where, $CoVaR_q^{j|X^i=VaR_q^i}$ and $CoVaR_q^{j|X^i=VaR_{50}^i}$ represent the *CoVaR* of institution *j* or the financial system when institution *i* is at its *q*% *VaR* (in distress) and when institution *i* is at its 50% *VaR* (median state), respectively. $\Delta CoVaR_q^{j|i}$ measures tail dependency, being able to capture spillover effects and common exposures. The remaining of the dissertation simplifies the notation to $CoVaR_q^{j|i}$ and $\Delta CoVaR_q^{j|i}$.

As mentioned in the literature review section (2.2.2) the general direction of conditioning in *CoVaR* and $\Delta CoVaR$ refers to *j* as financial system and *i* as an individual institution. Nevertheless, due to the directional property of *CoVaR*, two other directions for *CoVaR* can be derived, *Exposure-CoVaR,* where *j* stands for an individual institution and *i* for the system, and *Network-CoVaR,* whenever both *j* and *i* refer to individual institutions.

3.2. *VaR*

VaR is generally defined as the maximum percentage loss that a single institution or a portfolio can incur over a given period (h) within a specific confidence interval $(1-\alpha)$. Statistically speaking is simply the *q*% quantile, i.e.,

$$\Pr(X^i \leq -VaR_q^i) = q\%, \qquad (3)$$

where X^i represents the returns or losses of institution i for which VaR_q^i is defined. The choice of the confidence level $(1-\alpha)$ depends on regulations or on the risk aversion of the user (Alexander, 2008). A lower α significance level and *q*% quantile, or a higher $(1-\alpha)$ confidence level, generally define a more conservative user. As the terminology α is also be used for the quantile regression estimation of *CoVaR*, this dissertation avoids its use and employ the *q*% quantile and the confidence level instead. Regarding the risk horizon *h*, it represents the time over which the *VaR* is estimated.

3.2.1. Volatility Adjusted Historical VaR

Alexander (2008) splits *VaR* models into three basic types, the normal linear *VaR* model, the historical simulation model and the Monte Carlo *VaR*, which differ according to the way the discounted return distribution is constructed. Generally speaking, the historical simulation method relies heavily on past data, assuming that all possible scenarios have occurred in the past and that the historically simulated distribution is identical to the return's distribution over the future (Alexander, 2008). Therefore, the 100α% *h*-day historical *VaR* is simply the *q*% quantile of the historically simulated distribution.

Perhaps the greatest advantage of this method, comparing to normal linear *VaR* and Monte Carlo *VaR*, is the fact it makes few distributional assumptions. On the other hand, one of the greatest limitations is that it requires a large sample size and market circumstances change frequently over time (Alexander, 2008). The volatility adjusted historical *VaR*, suggested by Duffie and Pan (1997) and Hull and White (1998), overcome this limitation by adjusting the historical volatility to its current volatility and consequently improving the sensitivity of the historical *VaR* to current market conditions. To do so, a time series of volatility estimates for the historical sample is obtained, for example using a GARCH or EWMA model. This dissertation applies a GARCH model to adjust the time series of returns for the computation of the historical *VaR*, needed to estimate *CoVaR* (3.3.2).

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, proposed by Bollerslev (1986) as a generalization of the ARCH model, considers that the conditional variance of the error term is not constant but depends on the size of past error terms and variance level, and tries to capture changing volatility and volatility clustering. To obtain a time series of GARCH(1,1) volatility estimates $\hat{\sigma}_t^2$, we employ a AR(1) model for the returns,

$$X_t = \mu + \rho X_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2), \qquad (4)$$

and a model for the conditional volatility,

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \omega > 0, \alpha > 0, \beta > 0, \alpha + \beta < 1. \qquad (5)$$

Then, all model parameters ($\mu, \rho, \omega, \alpha$ and β) are estimated simultaneously using a technique called Maximum Likelihood Estimation (MLE), which aims to find the parameters' values that maximize the following log likelihood function,

$$\mathcal{L} = \sum_{t=1}^{n} ln\left(\frac{e^{-\frac{1}{2}\left(\frac{\varepsilon_t}{\sigma_t}\right)^2}}{\sqrt{2\pi}\sigma_t}\right) = \sum_{t=1}^{n}\left(-\frac{1}{2}\left(\frac{\varepsilon_t}{\sigma_t}\right)^2 - ln\sigma_t\right). \qquad (6)$$

The financial institutions' and Index's returns are computed using daily logarithmic returns (*equation 15)*, and the model for the returns (*equation 4*) is transformed to find the time series of errors. Consequently, *equation 5* is used to estimate the time series of GARCH volatilities $\hat{\sigma}_t^2$, and the volatility adjusted returns series is obtained by multiplying the return at every time $t < T$ by the GARCH volatility estimated at time T

divided by the GARCH volatility estimated at every time $t < T$, i.e.,

$$\tilde{X}_{t,T} = \left(\frac{\hat{\sigma}_T}{\hat{\sigma}_t}\right) X_t. \qquad (7)$$

3.3. Quantile Regression

Although *CoVaR* might be estimated through other methods – e.g. GARCH, copulas, Bayesian inference, maximum likelihood techniques, among others – Adrian and Brunnermeier (2008) present a methodology for estimating *CoVaR* relying on quantile regression, as they consider it a particular numerically efficient method, characterized by its simplicity and by not implying distributional assumptions. Likewise, this dissertation relies on the same estimation method.

Quantile regression, firstly proposed by Koenker and Basset (1978), models the relationship between an explanatory variable (or a set of explanatory variables) and specific quantiles of the dependent variable's probability distribution. This method is an extension and robust alternative to the Ordinary Least Squares (OLS) regression, as the last only estimates how the variation of a dependent variable's or a set of explanatory variables' mean influence the mean of the dependent variable. When estimating *CoVaR* and Δ*CoVaR*, we rely on low quantiles for the distress of institutions or the system, and therefore quantile regression is convenient.

In contrast with the OLS regression, it is not feasible to derive a formula for the quantile regression coefficients. Nonetheless, the majority of statistical software have quantile regression packages available. For the purpose of this dissertation, we use R Studio, an open software project freely downloaded from the CRAN website. An implementation of quantile regression in R language is available in the package "quantreg", developed by Roger Koenker (2011), and a tutorial introduction to the package is described in Koenker (2019). For this reason, we only present a brief overview of quantile regression and for a deeper understanding one should see Koenker and Bassett (1978). Suppose we have the following linear regression,

$$y_t = \hat{\alpha} + \hat{\beta} x_t, \qquad (8)$$

where x_t is a vector of predictors, and $\hat{\alpha}$ and $\hat{\beta}$ are quantile regression parameters. Then, $\hat{\alpha}$ and $\hat{\beta}$ can be determined as the solution for the following minimization problem,

$$(\hat{\alpha}, \hat{\beta}) = \min_{\alpha,\beta} \sum_{t=1}^{n} \varepsilon_t \left(q - I_{\varepsilon_t < 0}\right), e_t = y_t - (\alpha + \beta x_t). \tag{9}$$

The *equation 8* can now be used to predict the q^{th}-quantile of the dependent variable Y based on the value of the explanatory variable X.

3.3.1. Bootstrapping

We use bootstrapping for conducting inference about quantile regression coefficients. This technique requires sampling repeatedly with replacement from the actual data, in order to obtain a description of the empirical estimators' properties (Brooks, 2008), and is considered for several as the most suitable resampling method in quantile regression analysis (Davino, Furno and Vistocco, 2014). Even though it is a computational costly technique, it is currently available in several statistical software packages.

We use R Studio to compute bootstrapped standard errors applying the standard (x,y) pair bootstrap method, available in the "quantreg" package, developed by Roger Koenker (2011). The xy-pair method consists of constructing a given number of samples (*N*), generally with the same size as the original dataset, by randomly sampling with replacement from the original dataset (Davino et al., 2014). Considering the following quantile regression model,

$$y_t = \hat{\alpha} + \hat{\beta} x_t, \tag{10}$$

y_t and x_t are resampled simultaneously *N* times, and consequently *N* quantile regressions are determined, resulting in a vector of parameters. The standard error of that vector is useful as an estimate of the quantile regression's standard error (Davino et al., 2014).

3.3.2. CoVaR Estimation via Quantile Regression

Adrian and Brunnermeier (2008) present the following methodology, relying on quantile regression, to estimate *CoVaR*. The predicted value of a quantile regression of the financial system returns $\hat{X}_q^{system}$ on a particular financial institution *i* for the *q%* quantile is

$$\hat{X}_q^{system|X^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i, \tag{11}$$

where $\hat{X}_q^{system|X^i}$ refers to the predicted return value for a *q%*-quantile of the financial system conditional on the return X^i of institution *i*. Based on the definition of *VaR*, Adrian and Brunnermeier (2008) deduced that the predicted return value $\hat{X}_q^{system|X^i}$ provides the value of $CoVaR_q^{system|X^i}$, i.e.,

$$CoVaR_q^{system|X^i} = \hat{X}_q^{system|X^i}. \tag{12}$$

Therefore, the literature on quantile regression estimation of *CoVaR*, formally defines the value at risk of the financial system conditional on institution *i* as

$$CoVaR_q^{system|X^i} = VaR_q^{system|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i. \tag{13}$$

Consequently, institution *i*'s contribution to the systemic risk of the financial system, i.e. Δ*CoVaR*, is defined as

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{system|VaR_{50}^i} = \hat{\beta}_q^i\left(VaR_q^i - VaR_{50}^i\right). \tag{14}$$

4. Empirical Application

The empirical application of this dissertation focus on measuring systemic risk in the Southeast Asian banking system. That is, applying Adrian's and Brunnermeier's (2008) *CoVaR* methodology, we pretend to analyse the contribution of banking institutions to the systemic risk of the Southeast Asian financial system, to determine which banking institutions are more at risk if a financial crisis occurs in Southeast Asia, and to explore financial linkages across the network of banking institutions in the Southeast Asia. In this section, the data collected for this research is described (4.1) and the results are presented and analysed (4.2).

4.1. Data

This section provides an overview of how we select and collect the data sample (4.1) for the empirical application of this dissertation. Additionally, the descriptive statistics of the collected data's logarithmic returns are presented and analysed (4.2).

4.1.1. Data Selection and Collection

The empirical application of this dissertation focus on the major banking institutions in the Southeast Asian financial market. According to the FTSE ASEAN Index Series at the 31st of October 2019 (see *Table 1*), the top 10 constituents of the FTSE ASEAN All-Share Index[1] includes 6 banks, the DBS Group Holdings (D05.SI), the Oversea-Chinese Banking (O39.SI) and the United Overseas Bank (U11.SI), from Singapore; the Public Bank BHD (PUBM.KL), from Malaysia; and the Bank Central Asia (BBCA.JK) and the Bank Rakyat Indonesia (BBRI.JK), from Indonesia.These banking institutions and the FTSE ASEAN All-Share Index (FTASEANAS), which we choose as a proxy for the financial system, are then the variables selected for this research. The banking sector has 49 constituents in the FTSE ASEAN All-Share Index and is the sector with the highest weight in the Index (27,12% in the 31st of October 2019).

The data collected are the daily adjusted closing prices of the 6 banking institutions and the FTSE ASEAN All-Share Index itself, covering the period from the 31st of October

[1] Index representing the performance of large, mid and small cap listed companies from the seven leading ASEAN financial markets: Bursa Malaysia, Hanoi Stock Exchange, Ho Chi Minh Exchange, Indonesia Stock Exchange, The Philippine Stock Exchange and the Stock Exchange of Thailand.

CONSTITUENT	COUNTRY	ICB SECTOR	NET MCAP (USDM)	WGT %
DBS GROUP HOLDING	Singapore	Banks	34,320	3,70
OVERSEA-CHINESE BANKING	Singapore	Banks	27,137	2,92
UNITED OVERSEAS BANK	Singapore	Banks	25,279	2,72
BANK CENTRAL ASIA	Indonesia	Banks	21,588	2,33
PTT	Thailand	Oil & Gas Producers	21,406	2,31
SINGAPORE TELECOMMUNICATIONS	Singapore	Mobile Telecommunications	18,007	1,94
BANK RAKYAT INDONESIA	Indonesia	Banks	15,846	1,71
PUBLIC BANK BHD	Malaysia	Banks	15,028	1,62
TELEKOMUNIKASI INDONESIA	Indonesia	Fixed Line Telecommunications	13,568	1,46
CP ALL	Thailand	Food & Drug Retailers	13,461	1,45
TOTALS			205,638	22,15

Table 1- Top 10 constituents of FTSE ASEAN All Share Index. *Notes:* This table presents the top 10 constituents of the FTSE ASEAN All-Share Index on the 31st of October 2019. The cells in blue represent the financial institutions used as variables for this dissertation. Source: FTSE ASEAN Index Series

2014 to the 31st of October 2019. The choice of the period is mainly due to the Index launch in 2014. All the values are obtained from the *yahoo finance* website, excepting the Public Bank BHD's and the FTSE ASEAN All-Share Index's historical data which, due to missing data and odd values, are collected from the *investing.com* website. In order to formulate a time series, the working days' missing values of the stock market data are computed using linear interpolation. Consequently, the daily returns of each banking institution X^i and the Index $X^{FTASEANAS}$ can be calculated accordingly for the entire sample period. The formula is given as follows:

$$X_t = ln\left(\frac{P_t}{P_{t-1}}\right) = ln(P_t) - ln(P_{t-1}), \qquad (15)$$

where X_t is the daily return at time *t*, P_t is the adjusted closing price at time *t* and P_{t-1} is the adjusted closing price at the previous period.

	OBS.	MEAN	MIN	MAX	STD.DEV	SKEW.	KURT.	J-B
FTASEANAS	1304	-0,00007	-0,05449	0,03419	0,00688	-0,32386	7,8609	1294,1 (0,000)
BBCA.JK	1304	0,00072	-0,06074	0,06832	0,01215	0,04999	6,6482	716,32 (0,000)
BBRI.JK	1304	0,00088	-0,08052	0,17336	0,01888	0,00036	11,9188	4405,4 (0,000)
D05.SI	1304	0,0004	-0,05683	0,05186	0,01085	0,13178	4,8894	195,31 (0,000)
O39.SI	1304	0,00022	-0,04495	0,04154	0,00995	-0,04475	4,8588	185,81 (0,000)
PUBM.KL	1304	0,00007	-0,03279	0,04535	0,00628	0,04258	10,683	3179,2 (0,000)
U11.SI	1304	0,00026	-0,05348	0,03704	0,01024	-0,15905	4,6217	146,47 (0,000)

Table 2- Descriptive Statistics. *Notes:* This table presents the descriptive statistics of the Index and banking institutions' daily log returns. The numbers in parenthesis on the Jarque-Bera column are the *p*-values that test the null hypothesis of normal distribution.

4.1.2. Descriptive Statistics

The descriptive statistics of the six banking institutions and FTSE ASEAN All-Share Index are presented in *Table 2*. The number of observations would vary according to different trading days for each market, nonetheless the linear interpolation of missing values turns the number of observable returns equal. All the variables exhibit a sample mean close to zero and positive, excepting the FTASEANAS Index, whose sample mean is negative. The banking institutions from Indonesia (BBCA.JK and BBRI.JK) are the variables with higher mean return, followed by the ones from Singapore (D05.SI, O39.SI and U11.SI) and finally Malaysia (PUBM.KL). On the other hand, BBCA.JK and BBRI.JK are at the same time the institutions with significantly larger difference between the maximum and minimum returns, in contrast with PUBM.KL. Regarding the standard deviations, which represent a measure of financial risk, Indonesian banking institutions indicate a higher volatility, followed by Singaporean institutions and lastly the Malaysian institution. Thus, the descriptive statistics show evidence that the institutions with higher mean return are the most volatile, and vice-versa. Concerning the institutions' and Index's returns normality, the values given by the kurtosis and skewness indicate that the institutions' and Index's returns are not normally distributed, given that the values are in most cases considerably different from 3 and 0, respectively. The FTASEAN Index, and

	$q = 5\%$		$q = 1\%$	
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$
BBCA.JK	-0,01077 (0,00000)	0,29926 (0,00000)	-0,01604 (0,00000)	0,35546 (0,00000)
BBRI.JK	-0,00979 (0,00000)	0,18643 (0,00000)	-0,01704 (0,00000)	0,11741 (0,00116)
D05.SI	-0,00933 (0,00000)	0,43269 (0,00000)	-0,01412 (0,00000)	0,30396 (0,00079)
O39.SI	-0,00862 (0,00000)	0,45797 (0,00000)	-0,01456 (0,00000)	0,55636 (0,00000)
PUBM.KL	-0,01048 (0,0000)	0,38436 (0,00000)	-0,01772 (0,00000)	0,41590 (0,00021)
U11.SI	-0,00931 (0,00000)	0,49563 (0,00000)	-0,01424 (0,00000)	0,48221 (0,00065)

Table 3 – Quantile Regression Coefficients. *Notes:* In this table we present the quantile regression estimates ($\hat{\alpha}$ and $\hat{\beta}$), where the entire sample of the FTASEANAS Index's daily returns are regressed on the entire sample of each bank's daily returns, for both the 5% and 1% quantiles. The respective *p*-values are in parenthesis and are obtained from the bootstrapped standard-errors (*N*=10000).

the banking institutions O39.SI and U11.SI have negative values for skewness, evidencing higher likelihood for negative returns. Moreover, a kurtosis value higher than 3 indicates a higher likelihood for extreme events, which means that every variable has fatter tails. The Jarque-Bera test reinforces the institutions' and Index's returns non-normality, once all the p-values are lower than the significance level of 5%, meaning that the null hypothesis of sample log returns' normality is rejected.

4.2. Presentation and Analysis of Results

Previously we described the quantitative methodologies employed in this dissertation and the data selected for the analysis of systemic risk in the Southeast Asian banking system. In this section, we present the results of VaR, $CoVaR$ and $\Delta CoVaR$, obtained through volatility adjusted historical data and quantile regression, and discuss them. We split the analysis in three sections, according to the direction of conditioning and research questions order. First, we present the general *CoVaR*, where the system is conditional on the distress of a financial institution (4.2.1); then the *Exposure-CoVaR* (4.2.2); and lastly, the *Network-CoVaR* (4.2.3).

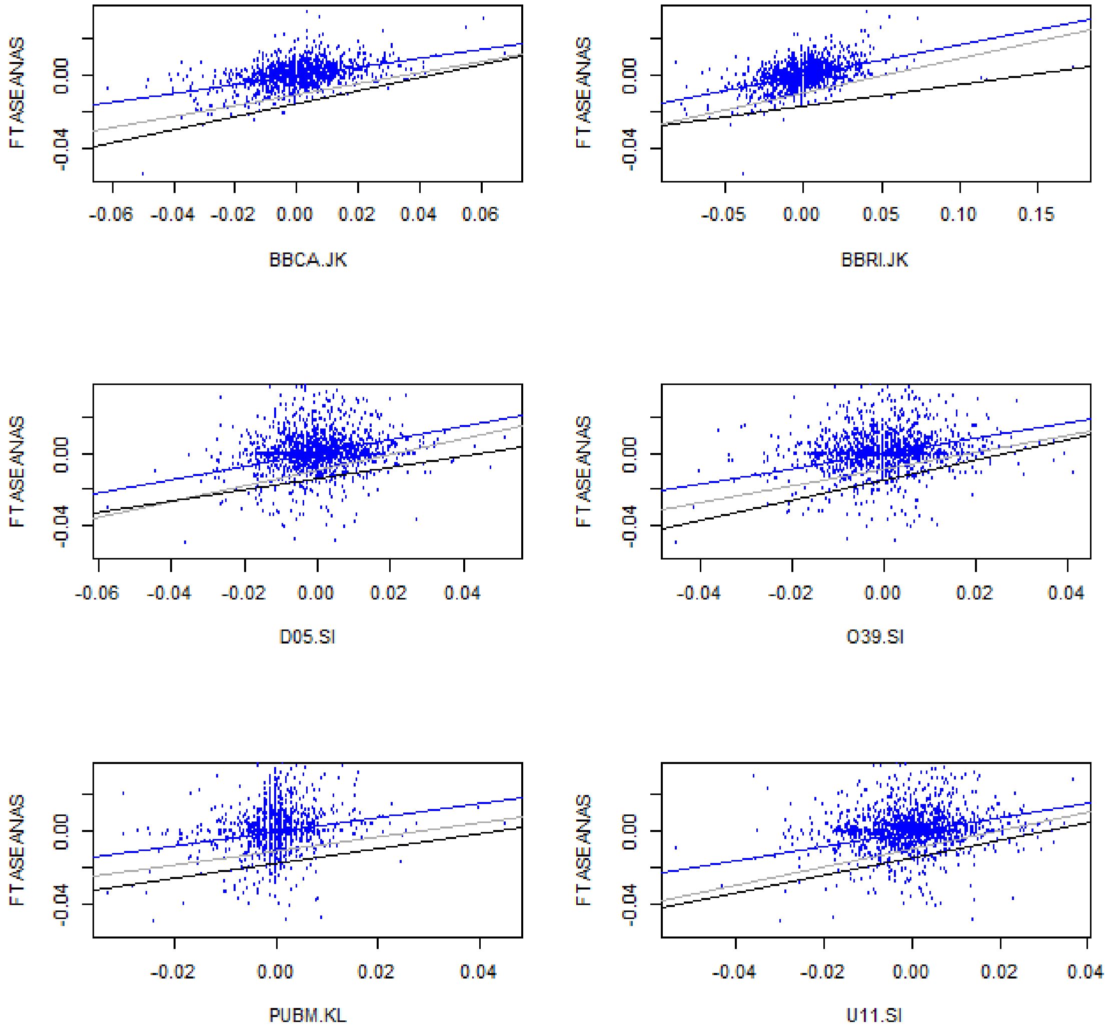
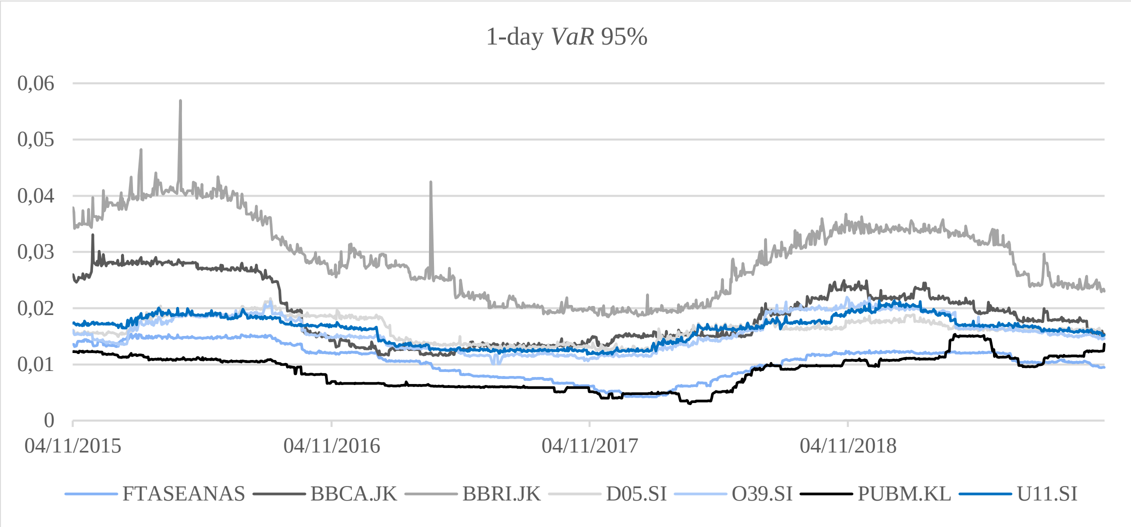


Figure 1- Quantile Regressions of The Index's Returns on Banks' Returns. *Notes:* This figure graphically presents the six quantile regressions of the entire sample of the FTASEAN Index's daily returns on the entire sample of each banking institution's daily returns for different quantiles. In blue points we represent the observations, in the blue line we present the OLS regression for comparison, in the grey line the 5% quantile regression, and in black the 1% quantile regression. Sample size= 1304.

4.2.1. *CoVaR*

In this section, we aim to analyse which of the six banking institutions contribute the most for the Southeast Asian systemic risk, and how the Southeast Asian *VaR* behaves conditional on the distress of each of them. Thus, we start by estimating how each individual institution's returns relate to specific quantiles of the Index's returns, and then we use those results and each banking institution's *VaR* in the *CoVaR* and Δ*CoVaR* estimation.



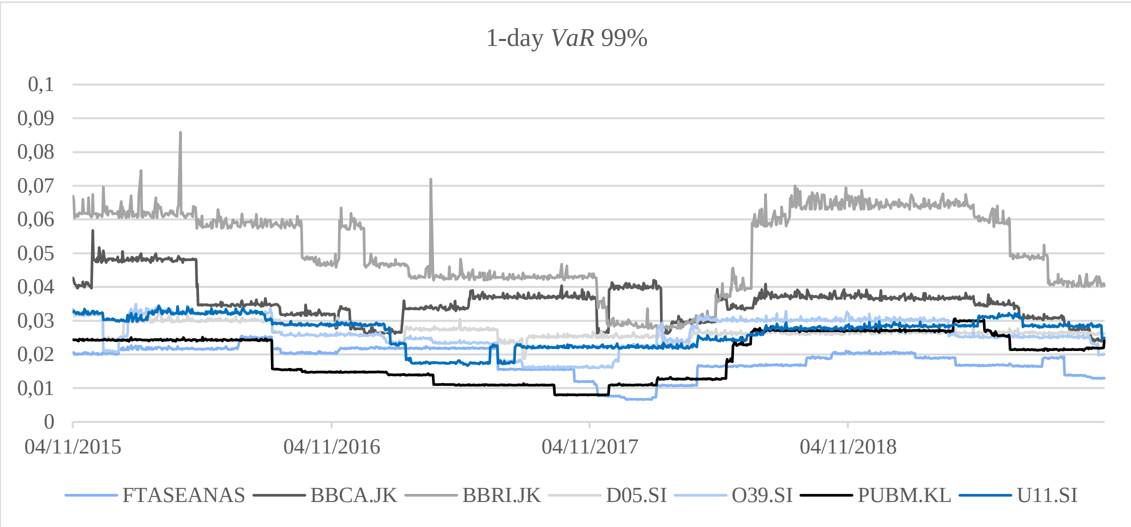


Figure 2 – Time series of 1-day *VaR*. *Notes:* This figure show the volatility adjusted historical 1-day *VaR*, estimated for each banking institutions and the Index, covering the period from the 4th of November 2005 to 1st of November 2019. The time series of returns were adjusted by applying a GARCH model. The 95% confidence *VaR* is presented above and the 99% confidence *VaR* is presented below.

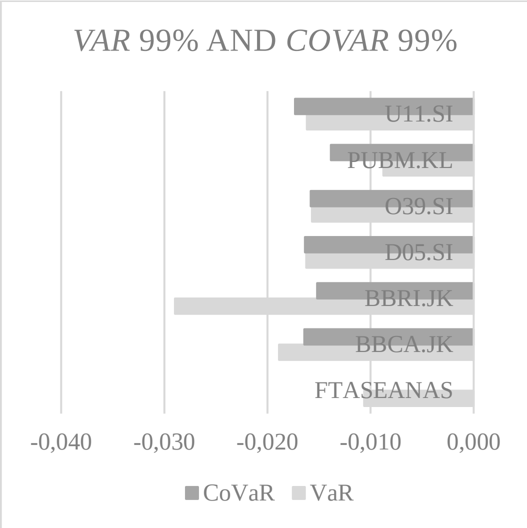
We develop six quantile regressions where the entire sample of FTASEANAS Index's daily returns is the dependent variable and the entire sample of banking institution's daily returns is the explanatory variable. Then, the quantile regression coefficients ($\hat{\alpha}$ and $\hat{\beta}$) are estimated for the 5% and 1% quantiles. To test the statistical relevance of the quantile regression estimates ($\hat{\alpha}$ and $\hat{\beta}$), we compute bootstrapped standard errors, applying the standard (x,y) pair bootstrap method with N=10000, which means that the Index's returns and the financial institution's returns are resampled 10000 times. The results for the

	$\boldsymbol{VaR}95\%$	$\boldsymbol{VaR}50\%$	$\boldsymbol{CoVaR}95\%$	$\boldsymbol{CoVaR}95\%$	$\boldsymbol{VaR}99\%$	$\boldsymbol{CoVaR}99\%$	$\Delta\boldsymbol{CoVaR}99\%$
FTASEANAS	0,01063	0,00007			0,01815		
BBCA.JK	0,01888	-0,00008	0,01642	0,00567	0,03578	0,02876	0,01275
BBRI.JK	0,02896	-0,00029	0,01519	0,00545	0,05124	0,02306	0,00605
D05.SI	0,01623	0,00008	0,01635	0,00699	0,02711	0,02236	0,00821
O39.SI	0,01569	-0,00015	0,01581	0,00726	0,02640	0,02925	0,01477
PUBM.KL	0,00875	0,00000	0,01384	0,00336	0,01943	0,02580	0,00808
U11.SI	0,01618	-0,00010	0,01733	0,00807	0,02670	0,02711	0,01292

Table 4- VaR, CoVaR and ΔCoVaR. *Notes:* In this table we present the 95%, 99% and 50% confidence Index's and banking institutions' *VaR*, and the 95% and 99% confidence *CoVaR* and Δ*CoVaR*. The *VaR* is an average of the estimated 1-day volatility adjusted historical *VaR*. The 95% and 99% confidence *CoVaR* are estimated through the estimated banking institution's *VaR* and quantile regression's coefficients of the entire sample of the FTASEANAS Index's daily returns on the entire sample of the banking institution's daily returns. Δ*CoVaR* is the difference between $CoVaR^{i}$ and $CoVaR^{i|median}$.

estimated bootstrapped standard errors are provided in *Table A1*. In *Table 3* we present the values for the estimated quantile regression coefficients ($\hat{\alpha}$ and $\hat{\beta}$) and their respective p-values for the 5% and 1% quantiles. According to the p-values obtained, all the slope coefficients ($\hat{\beta}$) are significantly different from zero and positive, rejecting the null hypothesis ($H_0\colon \beta = 0$) for both the 5% and 1% quantiles. We can therefore conclude that the banking institutions' returns have a positive and relevant influence on the Index's returns. The intercepts ($\hat{\alpha}$) are statistically significant as well. In addition, in *Figure 1* we graphically present the six quantile regressions for different quantiles, emphasising the positive relationship between the dependent and explanatory variables.

Then, we estimate the 1-day volatility adjusted historical *VaR* for every individual institution and Index, covering the period from 4th of November 2015 to 1st of November 2019. The results are estimated for a 95%, 99% and 50% confidence level, and for a risk horizon equal to one trading day. In *Figure 2* we represent the time-series of the estimated 1-day 99% and 95% *VaR* for the sample period and respective variables. As we focus on the cross-sectional component of systemic risk, an average of the sample period's *VaR*s is used for the *CoVaR* and Δ*CoVaR* estimation. In *Table 4* we present the Index's and banking institutions' average *VaR* estimates for the 5% and 1% quantiles.



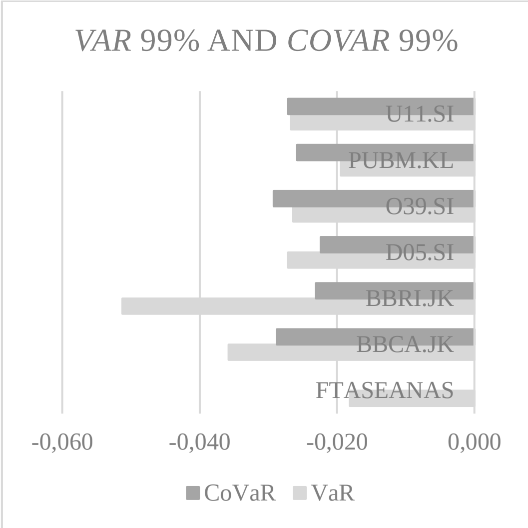


Figure 3- *VaR* and *CoVaR*. *Notes:* This figure presents a comparison between the banking institutions' and Index's *VaR* and respective *CoVaR*. The results for a 95% confidence level are presented on the left side and for a 99% confidence level on the right side. The variables' *VaR* are computed as an average of the sample period 1-day *VaR*. The *CoVaR* is estimated from the quantile regression of the entire sample of the FTASEANAS Index's daily returns on the entire sample of the bank's daily returns, and from the banking institution's *VaR*.

To reinforce, *VaR* is defined as the maximum percentage loss that a single institution or a portfolio can incur over a given period within a specific confidence interval. According to the *Table 4*, BBRI.JK is the banking institution with the highest 95% *VaR*. Indeed, we are 95% confident that, in average, the loss of BBRI.JK will not exceed 2,90% in one trading day. On the other hand, PUBM.KL is the banking institution with the lowest 95% *VaR*, and we are 95% confident that, on average, the loss of PUBM.KL will not exceed 0,88% in one trading day. Regardless of the confidence level, the financial institutions' *VaR* relative position is the same, nonetheless, the absolute values are obviously higher. *Table 4* shows that we are 99% confident that, in average, the loss of BBRI.JK will not exceed 5.12% in one trading day. Additionally, we are 99% confident that, in average, the loss of PUBM.KL will not exceed 1.94% in one trading day.

Regardless of the institution's individual risk, that same institution might be more or less risky for the system. That is, we may have an institution that in isolation is not very risky, but that contributes dangerously for the systemic risk of the financial system, and at the same time, a risky institution with a low contribution to the systemic risk. We previously examined the individual riskiness of the banking institutions through *VaR* estimation, next we then analyse their systemic riskiness, through *CoVaR* and Δ*CoVaR* estimation.

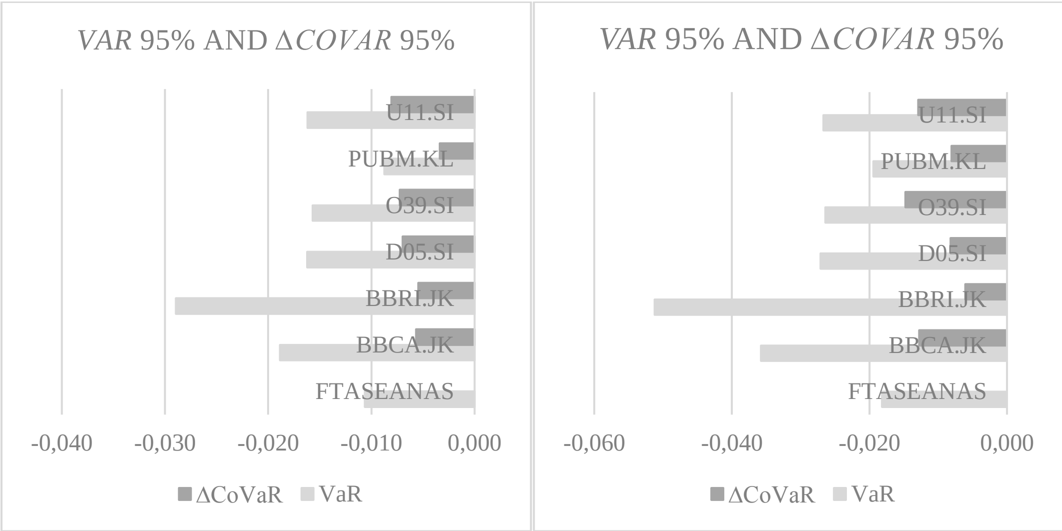


Figure 4- *VaR* and Δ*CoVaR*. *Notes:* This figure presents a comparison between the banking institutions' and Index's *VaR* and respective Δ*CoVaR*. The results for a 95% confidence level are presented on the left side and for a 99% confidence level on the right side. The variables' *VaR* are computed as an average of the sample period 1-day *VaR*. ΔCoVaR is the difference between $CoVaR^{i}$ and $CoVaR^{i|median}$.

From the quantile regression coefficients and estimated individual *VaR*s, we apply *Equation 13* and *Equation 14* and compute *CoVaR* and Δ*CoVaR*, respectively, for the FTSEASEANAS Index's returns conditional on each banking institution's returns. The values for the *CoVaR* and Δ*CoVaR* estimates are presented in *Table 4*. $CoVaR^{FTASEANAS|i}$ estimates the FTASEANAS Index's *VaR* conditional on the banking institution i being in distress, which we consider to be its 95% *VaR* and 99% *VaR* level. For instance, $CoVaR_{5\%}^{FTASEANAS|BBCA.JK}$= 1,64% means that the FTASEANAS Index's 95% *VaR* is equal to 1,64% when the banking institution BBCA.JK is at its 95% *VaR* level. *Figure 3* graphically represents the comparison between *VaR* and *CoVaR* estimates. As we can see, the FTASEANAS Index's *VaR* increases when the banking institutions are at their *VaR* levels, which suggest that interconnections are indeed present. Nonetheless, no particular institution seems to stand out.

Our main focus is on the contribution of the banking institutions to the systemic risk of the Index, i.e. on Δ*CoVaR*. $\Delta CoVaR^{FTASEANAS|i}$ determines how much the banking institution i contributes for the FTASEANAS Index's *VaR*, when that same institution

	$q = 5\%$		$q = 1\%$	
j	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$
BBCA.JK	-0,01670 (0,00000)	0,82504 (0,00000)	-0,03047 (0,00000)	1,00376 (0,00001)
BBRI.JK	-0,02426 (0,00000)	1,58281 (0,00000)	-0,04079 (0,00000)	1,72949 (0,00000)
D05.SI	-0,01329 (0,00000)	0,84841 (0,00000)	-0,02067 (0,00000)	1,16278 (0,00000)
O39.SI	-0,01229 (0,00000)	0,96347 (0,00000)	-0,01915 (0,00000)	0,92066 (0,00000)
PUBM.KL	-0,00894 (0,00000)	0,47665 (0,00000)	-0,01641 (0,00000)	0,56449 (0,00000)
U11.SI	-0,01356 (0,00000)	1,04807 (0,00000)	-0,02022 (0,00000)	1,09116 (0,00000)

Table 5- Quantile Regression Coefficients (Exposure *CoVaR*). *Notes*: This table presents the quantile regression estimates ($\hat{\alpha}$ and $\hat{\beta}$), where the entire sample of each bank's daily returns are regressed on the entire sample of the FTASEANAS Index's daily returns, for both the 5% and 1% quantile. The respective p-values are in parenthesis and are obtained from the bootstrapped standard-errors (*N*=10000).

moves from its median state to a distress situation. As an example, $CoVaR_{5\%}^{FTASEANAS|BBCA.JK}$= 0,57% means that FTASEANAS Index's 95% VaR increases in 0,57% when BBCA.JK moves from its median state (50% VaR) to its 95% VaR. For the 5% quantile, U11.SI, O39.SI and D05.SI are the institutions contributing the most for the Southeast Asian systemic risk, and BBCA.JK, BBRI.JK and PUBM.KL the institutions contributing the least. For the 1% quantile, O39.SI, U11.SI and BBCA.JK are the institutions contributing the most, and D05.SI, PUBM and BBRI.JK are the institutions contributing the least.

The results evidence that VaR can be misleading when measuring the systemic importance of a financial institution. Indeed, the riskiest institutions in isolation, might not be the riskiest when part of the system, and vice-versa. Despite being the banking institution with the highest VaR at both the 5% and 1% quantile, BBRI.JK is the least contributor for the Southeast Asian systemic risk at the 1% quantile. On the other hand, O39.SI and U11.SI, which individually are part of the institutions with the lowest VaR, represent the institutions contributing the most for the VaR of the Index when they move from their median state to their 95%VaR and 99%VaR level. In *Figure 4* we graphically present the banking institutions' and Index' VaR comparing to the respective contribution to the systemic risk.

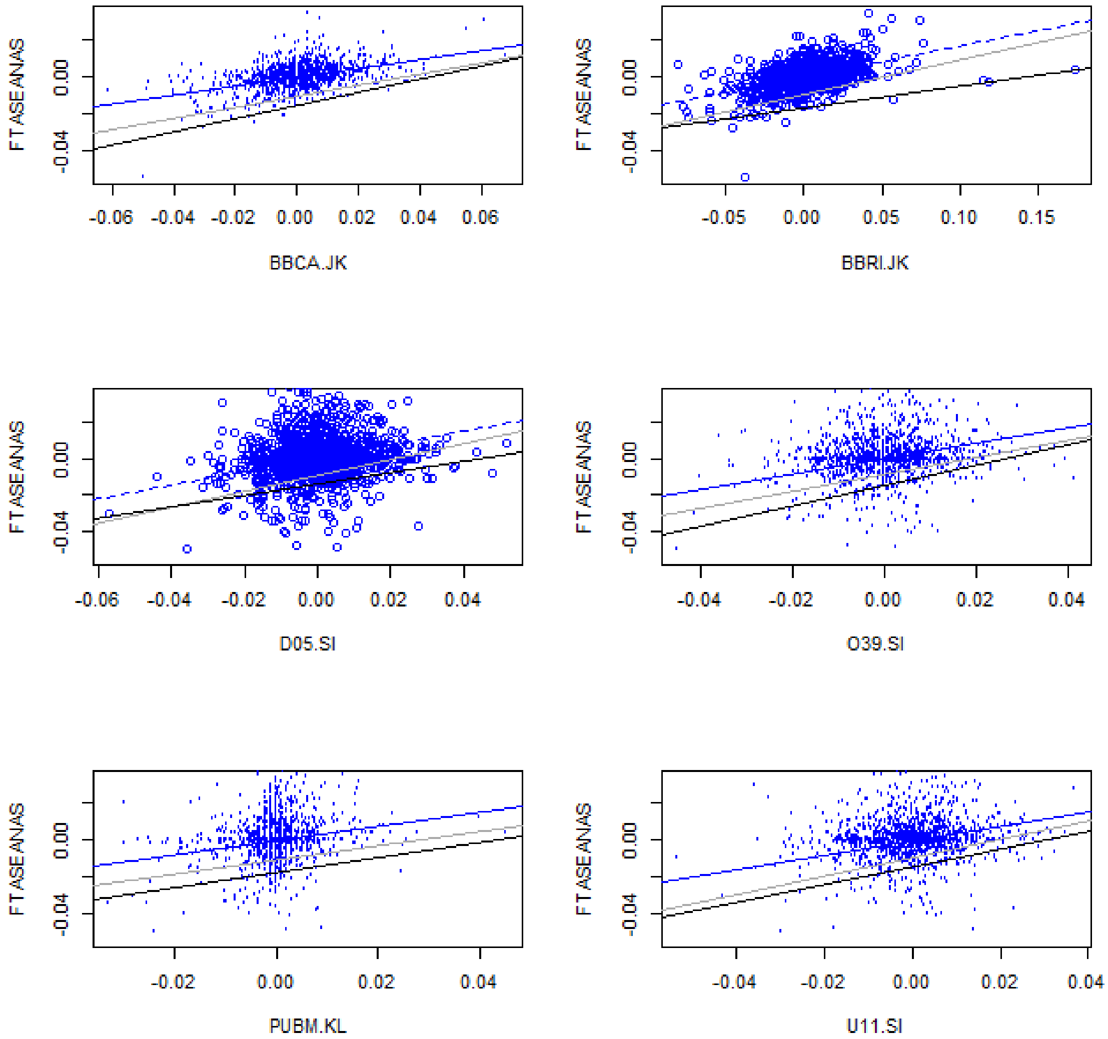


Figure 5- Quantile Regressions of The Bank's Returns on Index' Returns. *Notes:* This figure graphically presents the six quantile regressions of the entire sample of each banking institutions' daily returns on the entire sample of the FTASEANAS Index's daily returns for different quantiles. In blue points we represent the observations, in the blue line we present the OLS regression for comparison, in the grey line the 5% quantile regression, and in black the 1% quantile regression. Sample size= 1304.

4.2.2. *Exposure-CoVaR*

In contrast with the last section, here we aim to analyse how the Southeast Asian financial system affects each banking institution. Thus, we start by estimating how the Index's returns relates to specific quantiles of each individual institution's returns, and then we use those results and the Index's *VaR* in the *Exposure-CoVaR* and *Exposure-*Δ*CoVaR* estimation.

j	$CoVaR95\%$	$\Delta CoVaR95\%$	$CoVaR99\%$	$\Delta CoVaR99\%$
BBCA.JK	0,02547	0,00871	0,04869	0,01815
BBRI.JK	0,04108	0,01671	0,07219	0,03128
D05.SI	0,02230	0,00896	0,04178	0,02103
O39.SI	0,02253	0,01017	0,03586	0,01665
PUBM.KL	0,01400	0,00503	0,02666	0,01021
U11.SI	0,02470	0,01106	0,04003	0,01974

Table 6- *Exposure-CoVaR* and *Exposure-$\Delta CoVaR$*. *Notes*: This table presents the 95% and 99% confidence *Exposure-CoVaR* and *Exposure-$\Delta CoVaR$*. *Exposure-CoVaR* is estimated through the estimated FTASEANAS Index's *VaR* and quantile regression's coefficients of the entire sample of the banking institution's daily returns on the entire sample of the FTASEANAS Index's daily returns. Δ*CoVaR* is the difference between $CoVaR^{j|FTASEANAS}$ and $CoVaR^{j|FTASEAN(median)}$.

We develop six quantile regressions where the entire sample of a banking institution's daily returns is the dependent variable and the entire sample of FTASEANAS Index's daily returns is the explanatory variable. The quantile regression coefficients ($\hat{\alpha}$ and $\hat{\beta}$) are again estimated for the 5% and 1% quantiles of every relation and tested applying the same bootstrap technique. The results for the estimated bootstrapped standard errors are provided in *Table A3*. In *Table 5* we present the values for the estimated quantile regressions coefficients ($\hat{\alpha}$ and $\hat{\beta}$) and their respective *p*-values for the 5% and 1% quantiles. According to the *p*-values, all the slope coefficients ($\hat{\beta}$) are significantly different from zero and positive, for both the 5% and 1% quantiles, and thus we can conclude that the Index's returns have a positive and relevant influence on the banking institutions' returns.

In *Figure 5* we present the six quantile regressions for different quantiles. Once again, the positive relationship is also graphically evident and all the quantile regressions seem to converge at the end of the sample, meaning that their estimated slopes ($\hat{\beta}$) decrease for higher quantiles.

From the quantile regression coefficients and estimated Index's *VaRs*, we apply *Equation 13* and *Equation 14* and compute the *Exposure-CoVaR* and *Exposure-*Δ*CoVaR*, respectively. The values for the *Exposure-CoVaR* and *Exposure-*Δ*CoVaR* estimates are presented in *Table 6* for the 5% and 1% quantiles. $CoVaR^{j|FTASEANAS}$ estimates the banking institution's *VaR* conditional on the Index being in distress. *Figure 6* graphically

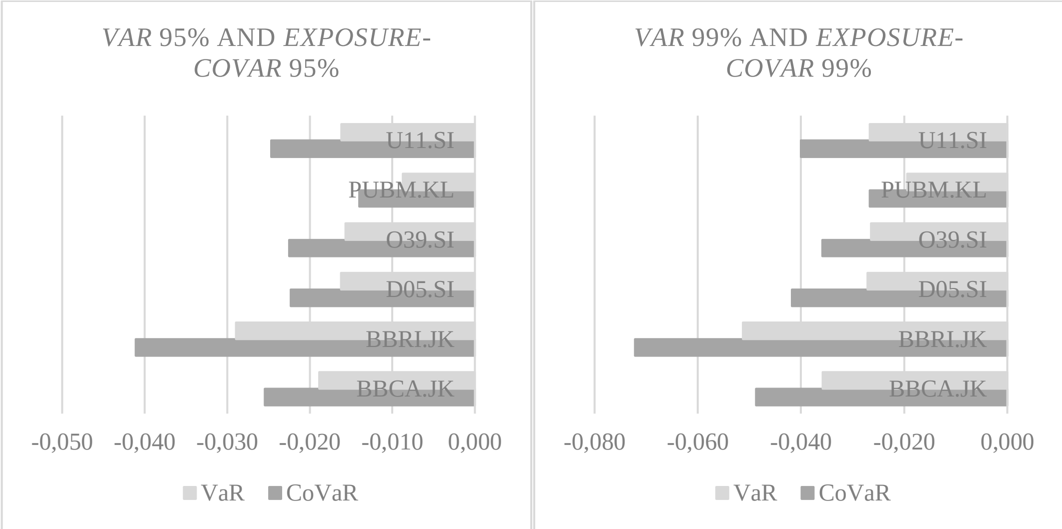


Figure 6- *VaR* and *Exposure-CoVaR*. *Notes:* This figure presents a comparison between the banking institutions' and FTASEANAS Index's *VaR* and respective *Exposure-CoVaR*. The results for a 95% confidence level are presented on the left side and for a 99% confidence level on the right side. The variables' *VaR* are computed as an average of the sample period 1-day *VaR*. The *Exposure-CoVaR* is estimated from the quantile regression of the entire sample of each baking institution's daily returns on the entire sample of the Index's daily returns, and from the Index's *VaR*.

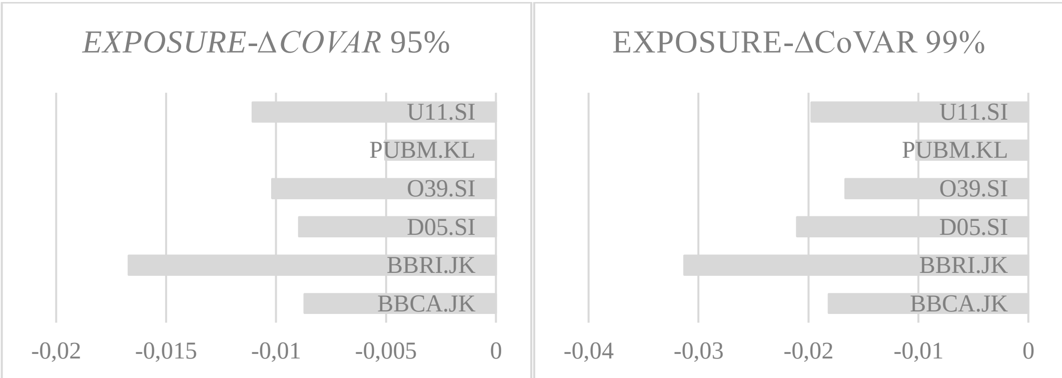


Figure 7- *Exposure*-Δ*CoVaR*. *Notes:* This figure presents the *Exposure*-Δ*CoVaR*, estimated from the quantile regression of the entire sample of each banking institution's daily returns on the entire sample of the FTASEANAS Index's daily returns, and from the Index's *VaR*. The *VaR* is computed as an average of the sample period 1-day *VaR*. The *Exposure*-ΔCoVaR is the difference between $CoVaR^{j|FTASEANAS}$ and $CoVaR^{j|FTASEANAS(median)}$.

represents the comparison between the banking institutions' *VaR* and *Exposure-CoVaR* estimates. The results indicate that the distress of Index influences negatively the *VaR* of the banking institutions, as expected. Nonetheless, no banking institution seems to be particularly reactive.

The *Exposure-*Δ*CoVaR* measures how sensitive a financial institution is to a financial crisis. According to *Figure 7*, for the 5% quantile, BBRI.JK, U11.SI and O39.SI are the institutions more at risk, and BBCA.JK, D05.SI and PUBM.KL are the less sensitive banking institutions in the event of a financial crisis in the Southeast Asian financial system. On the other hand, for the 1% quantile, BBRI.JK, D05.SI and U11.SI are the institutions more at risk, and BBCA.JK, O39.SI and PUBM.KL the least.

4.2.3. *Network-CoVaR*

Lastly, in this section we analyse financial linkages and interconnectedness between the banking institutions. Thus, we start by estimating how each banking institution's returns relates to specific quantiles of another baking institution's returns, and then we use those results and the institutions' *VaR* in the *Network-CoVaR* and *Network-*Δ*CoVaR* estimation.

We develop thirty quantile regressions where the entire sample of a banking institution's daily returns is the dependent variable and the entire sample of another banking institution's daily returns is the explanatory variable. The quantile regression coefficients ($\hat{\alpha}$ and $\hat{\beta}$) are estimated for the 5% and 1% quantiles and tested applying the same bootstrap technique. Only the quantile regressions whose slope coefficient ($\hat{\beta}$) is significantly different from zero are included in the further *Network-CoVaR* and *Network-*Δ*CoVaR* analysis. The quantile regression coefficients ($\hat{\alpha}$ and $\hat{\beta}$), and respective *p*-values are present in *Table A4* and *Table A5* for the 5% and 1% quantiles, respectively.

The *Network-CoVaR* and *Network-*$\Delta CoVaR$ are estimated based on those quantile regression coefficients and on each banking institution's *VaR*. In *Table A6* we present the *Network-CoVaR* and *Network-*$\Delta CoVaR$ values for both the 5% and 1% quantile. Similarly to *CoVaR* and *Exposure-CoVaR*, $CoVaR^{j|i}$ estimates the *VaR* of the banking institution *j* when the banking institution i is in distress, and $\Delta CoVaR^{j|i}$ measures how much the banking institution i contributes to institution j's *VaR* when the institution i moves from its median state to a distress situation.

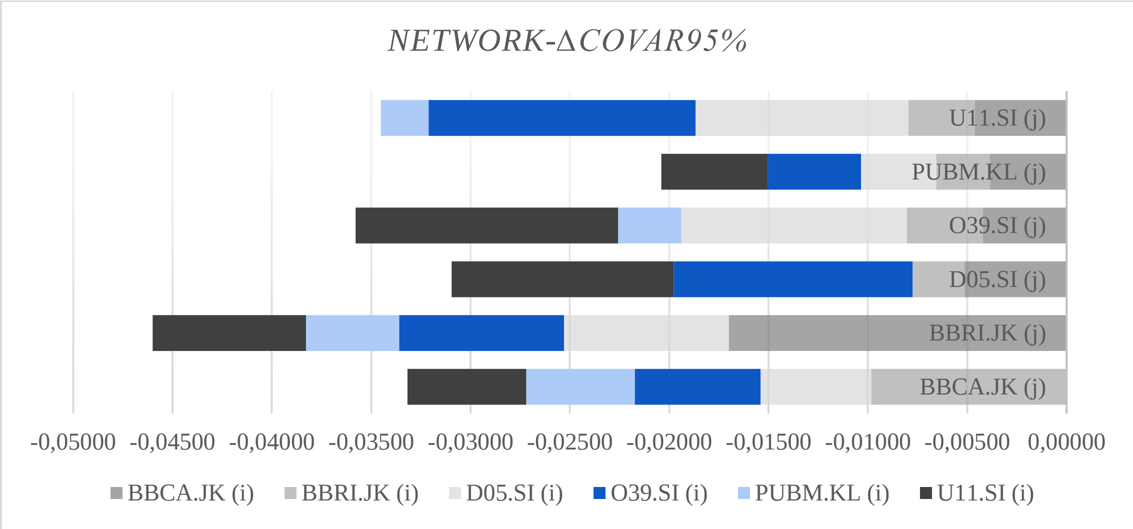


Figure 8- Network-ΔCoVaR95%. *Notes:* This figure presents the *Network-ΔCoVaR95%*, estimated from the 5% quantile regression of the entire sample of the banking institution j's daily returns on the entire sample of the banking institution i's daily returns, and from the banking institution i's *VaR*. The *VaR* is computed as an average of the sample period 1-day *VaR*. The *Network*-ΔCoVaR is the difference between $CoVaR^{j|i}$ and $CoVaR^{j|i(median)}$. In this figure, we only include the explanatory variables (i) whose slope coefficient, when regressing the dependent variable j's returns, is statistically significant.

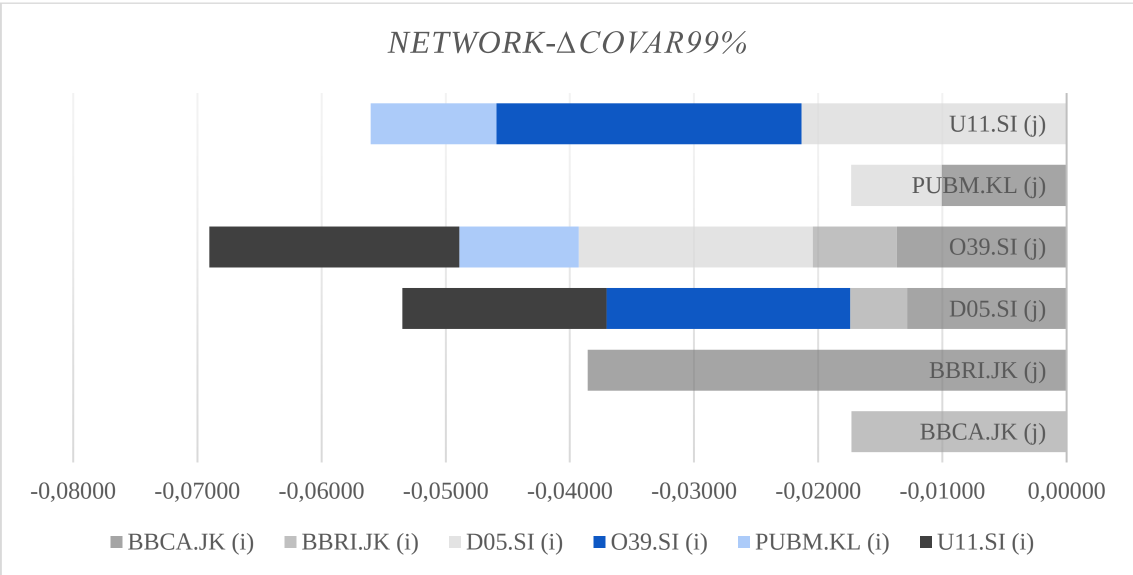


Figure 9- Network-ΔCoVaR99%. *Notes:* This figure presents the *Network-ΔCoVaR99%*, estimated from the 1% quantile regression of the entire sample of the banking institution j's daily returns on the entire sample of the banking institution i's daily returns, and from the banking institution i's *VaR*. The *VaR* is computed as an average of the sample period 1-day *VaR*. The *Network*-ΔCoVaR is the difference between $CoVaR^{j|i}$ and $CoVaR^{j|i(median)}$. In this figure, we only include the explanatory variables (i) whose slope coefficient, when regressing the dependent variable j's returns, is statistically significant.

In *Figure 8* and *Figure 9* we present the *Network*-$\Delta CoVaR$ values for the 5% and 1% quantiles, respectively. On the right side of the figures, we present the banking institution *j*, which stands for the dependent variable. For each dependent variable, we attribute different sizes and colours according to the systemic risk contribution and explanatory variable i. For instance, we are 95% confident that, when U11.SI is the dependent variable (j), O39.SI is the explanatory variable (i) contributing more for its systemic risk, followed by D05.SI, BBCA.JK, BBRI.JK and PUBM.KL.

According to the results obtained, we can conclude that there exist financial linkages and interconnectedness across the banking institutions, especially for the 5% quantile. At this quantile, the six banking institutions' *VaRs* are negatively affected when another banking institution moves from its median state to its 95% *VaR* level. The only exception happens when D05.SI's daily returns are regressed on PUBM.KL's daily returns, since the former is not significantly affected by the last. For the 1% quantile, there exist more statistically irrelevant relationships, in particular between institutions from different countries of origin (e.g. the Indonesian banking institutions are only affected by each other). This might indicate that the Southeast Asian economies and financial markets are not so integrated. Lastly, the major systemic risk contributions happen within institutions from the same country, as would be expectable (e.g. BBCA.JK is the riskiest institution to BBRI.JK, and vice-versa; O39.SI is the riskiest institution to D05.SI and U11.SI; and U11.SI is the riskiest institution to O39.SI).

5. Conclusion

This dissertation's main objective was to employ Adrian's and Brunnermeier's *CoVaR* methodology in the study of the cross-sectional level of systemic risk in the Southeast Asian banking system. In particular (i) to identify which banks contribute the most for the systemic risk of the Southeast Asian financial market; (ii) to determine which banks are more at risk if a financial crisis occurs in the Southeast Asia; (iii) and to evaluate and capture financial linkages and interconnectedness between the banks. With this in mind, we chose a sample of six banking institutions: DBS Group Holdings, Oversea-Chinese Banking, United Overseas Bank, Public Bank BHD, Bank Central Asia and Bank Rakyat Indonesia.

We found out, for the period from 4th of November 2015 to 1st of November 2019, (i) that the United Overseas Bank and the Oversea-Chinese Banking are the banking institutions contributing the most for the systemic risk of Southeast Asian financial market, and that the Bank Rakyat Indonesia and Public Bank BHD are the least contributors; (ii) that if a crisis does occur in the Southeast Asian financial market, the Indonesian banking institutions, i.e. the Bank Central Asia and the Bank Rakyat Indonesia, are the institutions more at risk, and on the other hand the Public Bank BHD, from Malaysia, is the least at risk; and lastly (iii) that there are financial linkages across the six banking institutions, especially for the 5% quantile. Nevertheless, for the 1% quantile, the cross-country interconnections are mostly irrelevant, which might indicate that the Southeast Asian economies and financial markets are not so integrated.

Additionally, we realized that the institutions with the highest individual risk, measured by *VaR*, are not necessarily the ones with the highest contribution to the Southeast Asian systemic risk ($\Delta CoVaR$). This corroborates with the idea that *VaR* might be a poor cross-sectional measure of systemic risk. Whereas, the results seem support the general assumption that bigger banking institutions usually contribute more for the systemic risk of the system, in particular for the 5% quantile.

This dissertation has limitations, which consequently enable us to make suggestions for further research. Firstly, we do not know which factors influence the interconnections across the variables, and so we cannot conclude if the certain factors, such as the size or the *VaR* of an institution, affect an institution's contribution to the systemic risk. Secondly, as we do not include state variables, the estimated interdependences might be a consequence of exogenous variables affecting the system and the banking institutions, and not of real interconnections. Those two limitations can be overcome by estimating the time varying *VaR* and *CoVaR*, also proposed by Adrian and Brunnermeier (2008), which estimates the systemic risk contribution as a function of macrostate variables. Thirdly, our analysis has a short sample period and does not cover any crisis period. One could then extend the entire sample period under analysis and, for instance, subdivide it in four sub periods, in order to compare the results before and after the Asian financial crisis of 1997 and the financial crisis of 2007-2009. And finally, our sample does not cover a large amount of banking institutions, not allowing us to analyze, for example, how the Index's *VaR* reacts conditional on the distress of smaller banking institutions. The major restriction would be though the data availability issues, which would restrict not only the time series analysis, but also the cross-sectional.

In summary, we contribute for the literature by measuring the systemic risk in the Southeast Asian banking system, but also by emphasizing the importance of measuring and monitoring interconnectedness and financial linkages. The literature on systemic risk in Southeast Asia is limited, nonetheless, this region is facing a strong economic growth and global integration, and therefore should be protected, and protect the other markets, against spillover effects and simultaneous failures.

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Appendix

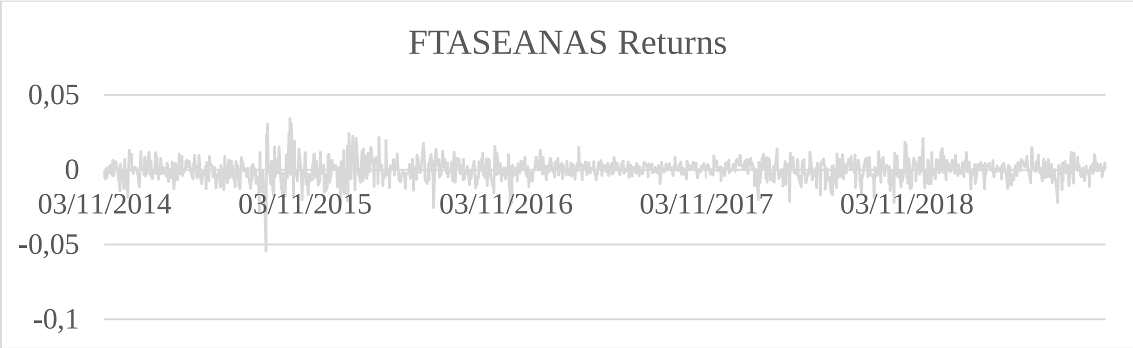

Figure A1- FTSE ASEAN All-Share's daily logarithmic returns.

Figure A2- BBCA.JK's daily logarithmic returns.

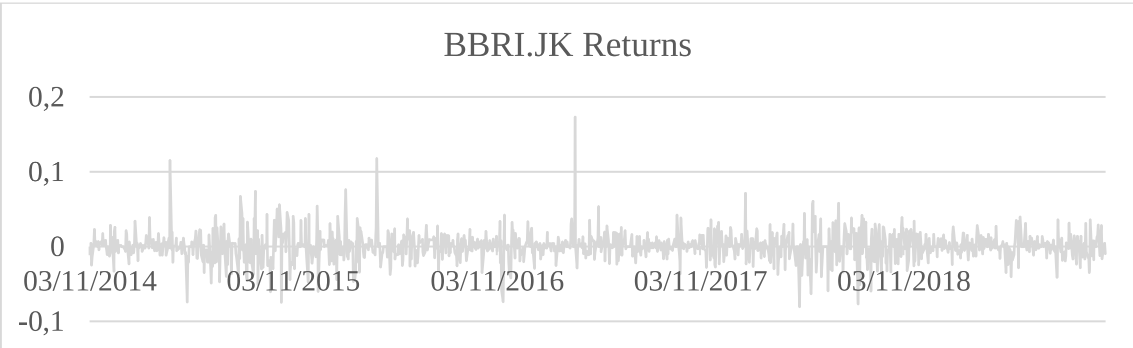

Figure A3- BBRI.JK's daily logarithmic returns.

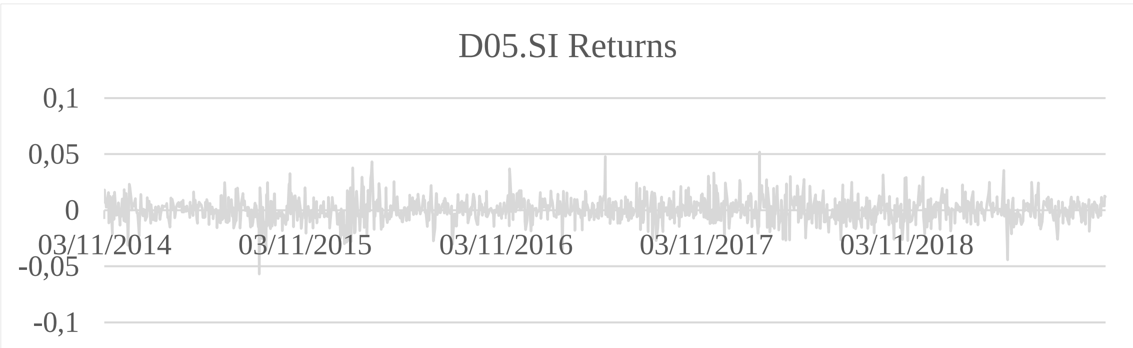

Figure A4- D05.SI's daily logarithmic returns.

Figure A5- O39.SI's daily logarithmic returns.

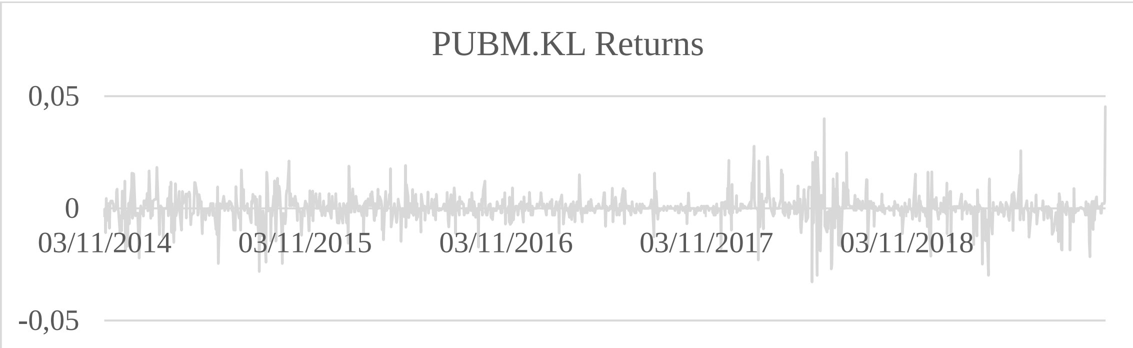

Figure A6- PUBM.KL's daily logarithmic returns.

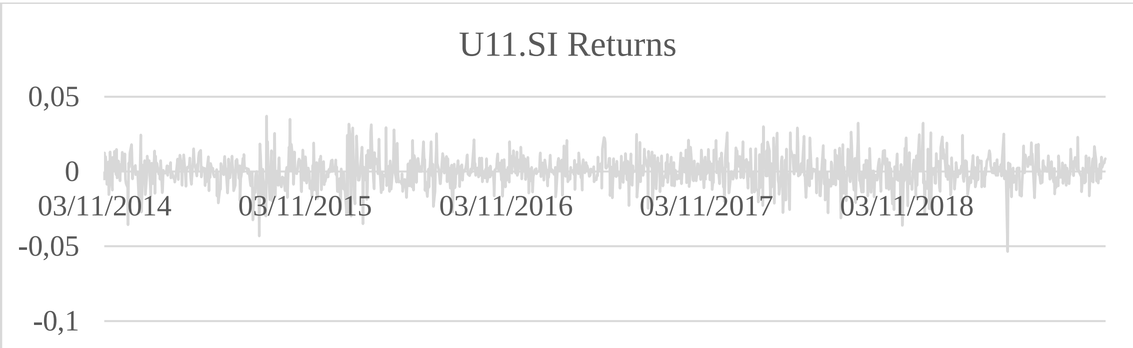

Figure A7- U11.SI's daily logarithmic returns

$$\widehat{X}_q^{FTASEANAS|X^i} = \widehat{\alpha}_q^i + \widehat{\beta}_q^i X^i, q = 5\%$$

	Value	Std. Error	Lower	Upper	t value	Pr(>|t|)
$\widehat{\beta}_{BBCA.JK}$	0,29926	0,0276	0,24406	0,35446	10,7797	0,00000
$\widehat{\alpha}_{BBCA.JK}$	-0,01077	0,00037	-0,01151	-0,01003	-28,961	0,00000
$\widehat{\beta}_{BBRI.JK}$	0,18643	0,03415	0,11813	0,25473	5,52242	0,00000
$\widehat{\alpha}_{BBRI.JK}$	-0,00979	0,00044	-0,01067	-0,00891	-22,316	0,00000
$\widehat{\beta}_{D05.SI}$	0,43269	0,02906	0,37457	0,49081	14,6397	0,00000
$\widehat{\alpha}_{D05.SI}$	-0,00933	0,00028	-0,00989	-0,00877	-33,691	0,00000
$\widehat{\beta}_{O39.SI}$	0,45797	0,02576	0,40645	0,50949	18,6936	0,00000
$\widehat{\alpha}_{O39.SI}$	-0,00862	0,00033	-0,00928	-0,00796	-25,977	0,00000
$\widehat{\beta}_{PUBM.KL}$	0,38436	0,06315	0,25806	0,51066	5,98068	0,00000
$\widehat{\alpha}_{PUBM.KL}$	-0,01048	0,00045	-0,01138	-0,00958	-23,496	0,00000
$\widehat{\beta}_{U11.SI}$	0,49563	0,045797	0,404036	0,587224	3,41535	0,00066
$\widehat{\alpha}_{U11.SI}$	-0,00931	0,00039	-0,01009	-0,00853	-23,994	0,00000

$$\widehat{X}_q^{FTASEANAS|X^i} = \widehat{\alpha}_q^i + \widehat{\beta}_q^i X^i, q = 1\%$$

	Value	Std. Error	Lower	Upper	t value	Pr(>|t|)
$\widehat{\beta}_{BBCA.JK}$	0,35546	0,04907	0,25732	0,4536	7,32162	0,00000
$\widehat{\alpha}_{BBCA.JK}$	-0,01604	0,00112	-0,01828	-0,0138	-14,367	0,00000
$\widehat{\beta}_{BBRI.JK}$	0,11741	0,03627	0,04487	0,18995	3,25625	0,00116
$\widehat{\alpha}_{BBRI.JK}$	-0,01704	0,0009	-0,01884	-0,01524	-18,887	0,00000
$\widehat{\beta}_{D05.SI}$	0,30396	0,09141	0,12114	0,48678	3,33951	0,00086
$\widehat{\alpha}_{D05.SI}$	-0,01412	0,0013	-0,01672	-0,01152	-10,878	0,00000
$\widehat{\beta}_{O39.SI}$	0,55636	0,07785	0,40066	0,71206	7,03119	0,00000
$\widehat{\alpha}_{O39.SI}$	-0,01456	0,00112	-0,0168	-0,01232	-12,913	0,00000
$\widehat{\beta}_{PUBM.KL}$	0,4159	0,11487	0,18616	0,64564	3,69877	0,00023
$\widehat{\alpha}_{PUBM.KL}$	-0,01772	0,00161	-0,02094	-0,0145	-11,04	0,00000
$\widehat{\beta}_{U11.SI}$	0,48221	0,14	0,20221	0,76221	3,41535	0,00066
$\widehat{\alpha}_{U11.SI}$	-0,01424	0,00191	-0,01806	-0,01042	-7,4648	0,00000

Table A1- Summary Quantile Regression. ***Notes:*** This table presents the coefficients estimated from the quantile regression of the entire sample of FTASEANAS Index's daily returns on the entire sample banking institution i's daily returns. The Standard Error, t value and *p*-value are compute applying the standard (x,y) pair bootstrap method with *N*=10000.

	MEAN	STD. DEV.	OBSERVATIONS
$\boldsymbol{VaR_{99,t}^{FTASEANAS}}$	-0,01815	0,000131	1043
$\boldsymbol{VaR_{95,t}^{FTASEANAS}}$	-0,01063	9,37E-05	1043
$\boldsymbol{VaR_{99,t}^{i}}$	-0,03111	0,000154	6358
$\boldsymbol{VaR_{95,t}^{i}}$	-0,01745	9,26E-05	6358
$\boldsymbol{\Delta CoVaR_{95,t}^{i}}$	-0,00986	5,37E-05	6358
$\boldsymbol{\Delta CoVaR_{95,t}^{i}}$	-0,00613	2,44E-05	6358

Table A2- Summary Statistics for the Estimated Risk Measures. *Notes:* This table describes the summary statistics for the 99% and 95% risk measures of the 6 banking institutions for daily data from 4th of November 2015 to 1st of November 2019. The banking institutions and Index's *VaRs* are obtained by volatility adjusted historical data. $\Delta CoVaR_t^i$ is the difference between $CoVaR_t^i$ and $CoVaR_t^{i|median}$, where $CoVaR_t^i$ is estimated through a *q*% quantile regression of the entire sample of the FTSEASEAN Index's daily returns on the entire sample of a banking institution's daily returns.

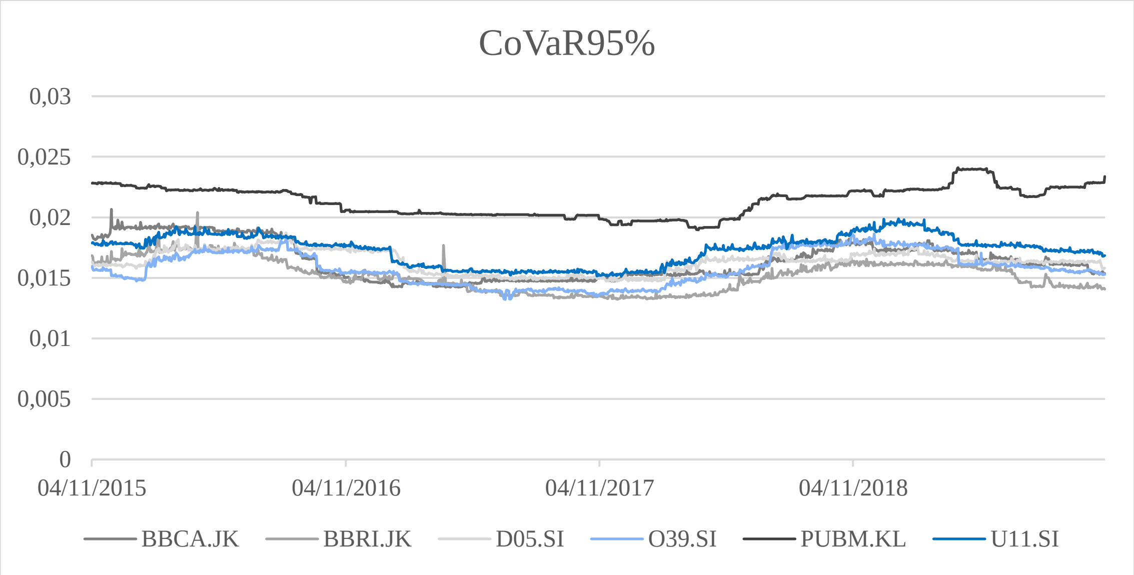

Figure A8- Time series of 1-day 95% *CoVaR*. *Notes:* This figure shows the 1-day 95% *CoVaR*, covering the period from the 4th of November 2005 to 1st of November 2019. The time-series was estimated using the banking institutions' 1-day volatility adjusted historical 95% *VaR*, and the coefficients from the quantile regression of the entire sample of the FTASEANAS Index's daily returns on the entire sample of the banking institution i's daily returns.

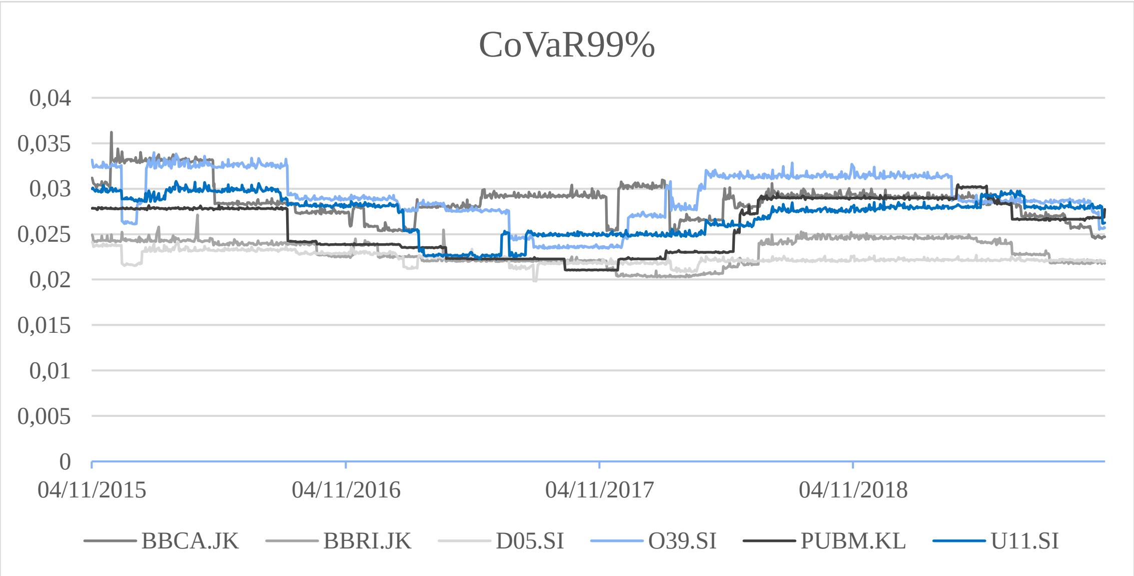

Figure A9- Time series of 1-day 99% *CoVaR*. *Notes:* This figure shows the 1-day 99% *CoVaR*, covering the period from the 4th of November 2005 to 1st of November 2019. The time-series was estimated using the banking institutions' 1-day volatility adjusted historical 99% *VaR*, and the coefficients from the quantile regression of the entire sample of FTASEANAS Index's daily returns on the entire sample of the banking institution i's daily returns.

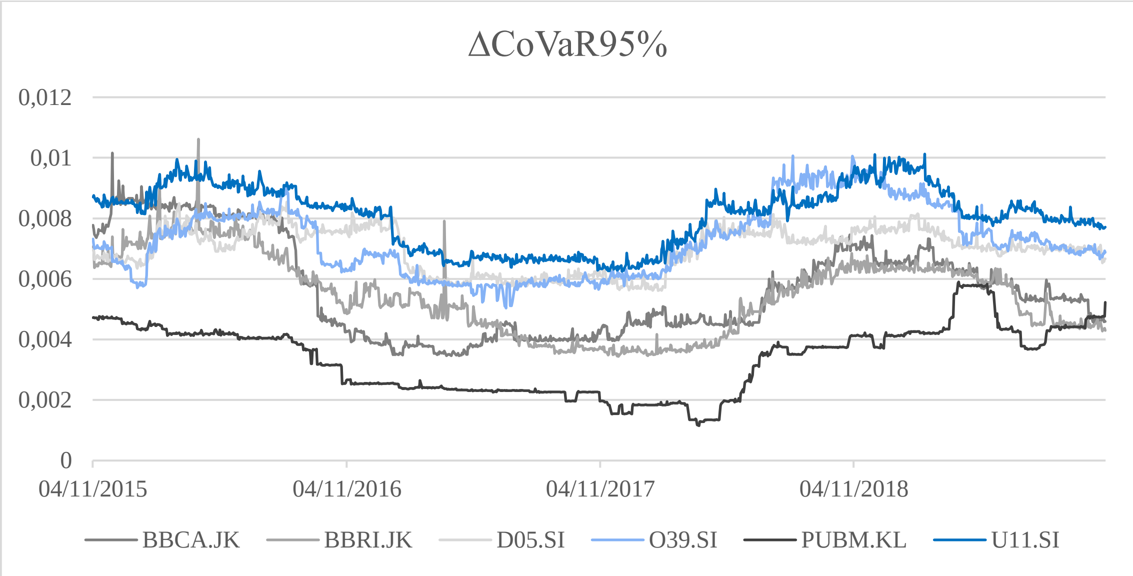

Figure A10- Time-series of 1-day 95% Δ*CoVaR*. *Notes:* This figure shows the 1-day 95% Δ*CoVaR*, covering the period from the 4th of November 2005 to 1st of November 2019. ΔCoVaR is the difference between CoVaR^{i} and $\mathrm{CoVaR}^{i|median}$.

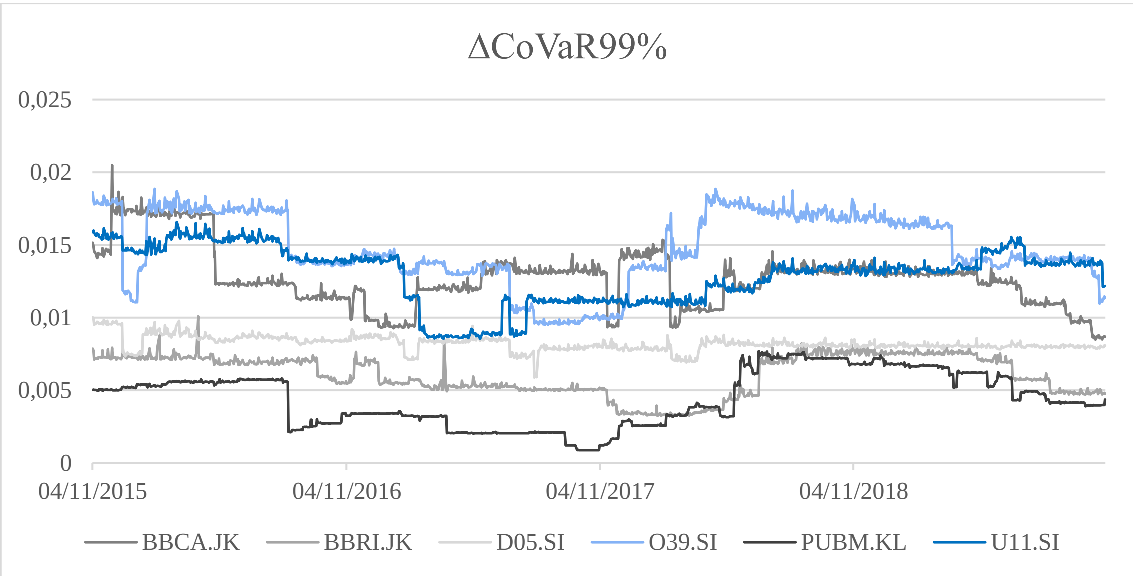

Figure A11 - Time series of 1-day 99% ΔCoVaR. *Notes:* This figure shows the 1-day 99% Δ*CoVaR*, covering the period from the 4th of November 2005 to 1st of November 2019. ΔCoVaR is the difference between CoVaR^{i} and $\mathrm{CoVaR}^{i|median}$.

$$\widehat{X}_q^{j|X^{FTASEANAS}} = \widehat{\alpha}_q^{FTASEANAS} + \widehat{\beta}_q^{FTASEANAS} X^{FTASEANAS}, q = 5\%$$

	Value	Std. Error	Lower	Upper	t value	Pr(>|t|)
$\widehat{\beta}_{BBCA.JK}$	0,82504	0,08028	0,66448	0,98560	10,27690	0,00000
$\widehat{\alpha}_{BBCA.JK}$	-0,0167	0,00104	-0,01878	-0,01462	-16,12365	0,00000
$\widehat{\beta}_{BBRI.JK}$	1,58281	0,18846	1,20589	1,95973	8,39858	0,00000
$\widehat{\alpha}_{BBRI.JK}$	-0,02426	0,00104	-0,02634	-0,02218	-23,24119	0,00000
$\widehat{\beta}_{D05.SI}$	0,84841	0,09043	0,66755	1,02927	9,38193	0,00000
$\widehat{\alpha}_{D05.SI}$	-0,01329	0,00079	-0,01487	-0,01171	-16,75104	0,00000
$\widehat{\beta}_{O39.SI}$	0,96347	0,06396	0,83555	1,09139	15,06325	0,00000
$\widehat{\alpha}_{O39.SI}$	-0,01229	0,00051	-0,01331	-0,01127	-10,95339	0,00000
$\widehat{\beta}_{PUBM.KL}$	0,47665	0,08182	0,31301	0,64029	5,82563	0,00000
$\widehat{\alpha}_{PUBM.KL}$	-0,00894	0,00070	-0,01034	-0,00754	-12,76618	0,00000
$\widehat{\beta}_{U11.SI}$	1,04807	0,07197	0,90413	1,19201	14,56264	0,00000
$\widehat{\alpha}_{U11.SI}$	-0,01356	0,00055	-0,01466	-0,01246	-24,48009	0,00000

$$\widehat{X}_q^{j|X^{FTASEANAS}} = \widehat{\alpha}_q^{FTASEANAS} + \widehat{\beta}_q^{FTASEANAS} X^{FTASEANAS}, q = 1\%$$

	Value	Std. Error	Lower	Upper	t value	Pr(>|t|)
$\widehat{\beta}_{BBCA.JK}$	1,00376	0,23040	0,54296	1,46456	4,35668	0,00001
$\widehat{\alpha}_{BBCA.JK}$	-0,03047	0,00346	-0,03739	-0,02355	-8,80375	0,00000
$\widehat{\beta}_{BBRI.JK}$	1,72949	0,29389	1,14171	2,31727	5,88486	0,00000
$\widehat{\alpha}_{BBRI.JK}$	-0,04079	0,00365	-0,04809	-0,03349	-11,16072	0,00000
$\widehat{\beta}_{D05.SI}$	1,16278	0,11186	0,93906	1,38650	10,39507	0,00000
$\widehat{\alpha}_{D05.SI}$	-0,02067	0,00119	-0,02305	-0,01829	-17,37230	0,00000
$\widehat{\beta}_{O39.SI}$	0,92066	0,13411	0,65244	1,18888	6,86488	0,00000
$\widehat{\alpha}_{O39.SI}$	-0,01915	0,00175	-0,02265	-0,01565	-10,95339	0,00000
$\widehat{\beta}_{PUBM.KL}$	0,56449	0,09207	0,38035	0,74863	6,13120	0,00000
$\widehat{\alpha}_{PUBM.KL}$	-0,01641	0,00159	-0,01959	-0,01323	-10,32856	0,00000
$\widehat{\beta}_{U11.SI}$	1,09116	0,18740	0,71636	1,46596	5,82253	0,00000
$\widehat{\alpha}_{U11.SI}$	-0,02022	0,00179	-0,02380	-0,01664	-11,31600	0,00000

Table A3- Summary Quantile Regression (Exposure). ***Notes:*** This table presents the coefficients estimated from the quantile regression of the entire sample of the banking institution *j*'s daily returns on the entire sample of the FTASEANAS Index's daily returns. The Standard Error, t value and *p*-value are compute applying the standard (x,y) pair bootstrap method with *N*=10000.

q=5%												
Dependent Variable:	BBCA.JK		BBRI.JK		D05.SI		O39.SI		PUBM.KL		U11.SI	
	α	Β	α	β	α	β	α	β	α	β	α	β
BBCA.JK			-0,0162 (0,00000)	0,3362 (0,00000)	-0,0181 (0,00000)	0,3452 (0,00000)	-0,0182 (0,00000)	0,3989 (0,00000)	-0,018 (0,00000)	0,6251 (0,00000)	-0,0183 (0,00000)	0,3669 (0,00001)
BBRI.JK	-0,0272 (0,00000)	0,8969 (0,00000)			-0,027 (0,00000)	0,5135 (0,00000)	-0,027 (0,00000)	0,5232 (0,00000)	-0,028 (0,00000)	0,5372 (0,00601)	-0,0272 (0,00000)	0,4733 (0,00000)
D05.SI	-0,0166 (0,00000)	0,2716 (0,00000)	-0,0162 (0,00000)	0,089 (0,01974)			-0,0117 (0,00000)	0,7584 (0,00000)	-0,0165 (0,00000)	0,28068 (0,07333)	-0,0114 (0,00000)	0,6868 (0,00000)
O39.SI	-0,0151 (0,00000)	0,2216 (0,00001)	-0,0151 (0,00000)	0,1314 (0,00169)	-0,0101 (0,00000)	0,7034 (0,00000)			-0,0149 (0,00000)	0,363 (0,00023)	-0,01 (0,00000)	0,8108 (0,00000)
PUBM.KL	-0,0104 (0,00000)	0,2033 (0,00000)	-0,0104 (0,00000)	0,0927 (0,01698)	-0,0102 (0,00000)	0,2345 (0,00001)	-0,0093 (0,00000)	0,295 (0,00000)			-0,0097 (0,00000)	0,33 (0,00000)
U11.SI	-0,0166 (0,00000)	0,2432 (0,00038)	-0,0162 (0,00000)	0,1148 (0,0315)	-0,0111 (0,00000)	0,6626 (0,00000)	-0,0109 (0,00000)	0,848 (0,00000)	-0,0163 (0,00000)	0,2753 (0,03716)		

Table A4- 5% Quantile Regression Coefficients (Network). *Notes:* This table presents the quantile regression estimates ($\hat{\alpha}$ and $\hat{\beta}$), where the entire sample of the banking institution j's daily returns are regressed on the entire sample of the banking institution i's daily returns, for the 5% quantile. The respective p-values are in parenthesis and are obtained from the bootstrapped standard-errors (*N*=10000). In blue we highlight the statistically irrelevant coefficients.

q=1%												
Dependent Variable:	BBCA.JK		BBRI.JK		D05.SI		O39.SI		PUBM.KL		U11.SI	
	α	Β	α	β	α	β	α	β	α	β	α	β
BBCA.JK			-0,0309 (0,00000)	0,2627 (0,00274)	-0,03478 (0,00000)	-0,03998 (0,86796)	-0,03584 (0,00000)	0,30689 (0,14894)	-0,03343 (0,00000)	0,35185 (0,24513)	-0,03479 (0,00000)	-0,07934 (0,75364)
BBRI.JK	-0,0408 (0,00000)	1,0752 (0,00000)			-0,04906 (0,00000)	0,40105 (0,308)	-0,04651 (0,00000)	0,52323 (0,03219)	-0,05026 (0,00000)	0,42177 (0,26852)	-0,04903 (0,00000)	0,17598 (0,72231)
D05.SI	-0,0258 (0,00000)	0,3582 (0,00372)	-0,0263 (0,00000)	0,1458 (0,00058)			-0,0174 (0,00000)	0,7386 (0,00000)	-0,02614 (0,00000)	0,39471 (0,0145)	-0,0172 (0,00000)	0,8462 (0,00000)
O39.SI	-0,026 (0,00000)	0,3811 (0,00117)	-0,0261 (0,00000)	0,1811 (0,00006)	-0,0149 (0,00000)	0,6971 (0,00000)			-0,0261 (0,00000)	0,4957 (0,00338)	-0,0161 (0,00000)	0,7508 (0,00000)
PUBM.KL	-0,0198 (0,00000)	0,2804 (0,00011)	-0,01876 (0,00000)	0,1082 (0,01834)	-0,0178 (0,00000)	0,2698 (0,00137)	-0,019 (0,00000)	0,2224 (0,05153)			0,0176 (0,00000)	0,25824 (0,02423)
U11.SI	-0,02692 (0,00000)	0,31026 (0,10738)	-0,02683 (0,00000)	0,17615 (0,01201)	-0,0185 (0,00000)	0,7897 (0,00000)	-0,0164 (0,00000)	0,9251 (0,00000)	-0,0258 (0,00000)	0,5219 (0,00000)		

Table A5- 1% Quantile Regression Coefficients (Network). *Notes:* This table presents the quantile regression estimates ($\hat{\alpha}$ and $\hat{\beta}$), where the entire sample of the banking institution *j*'s daily returns are regressed on the entire sample of the banking institution *i*'s daily returns, for the 1% quantile. The respective *p*-values are in parenthesis and are obtained from the bootstrapped standard-errors (*N*=10000). In blue we highlight the statistically irrelevant coefficients.

$CoVaR^{j\|i}_{5\%}$						
j \ *i*	BBCA.JK	BBRI.JK	D05.SI	O39.SI	PUBM.KL	U11.SI
BBCA.JK		0,02598	0,02365	0,02450	0,02347	0,02423
BBRI.JK	0,04412		0,03532	0,03520	0,03270	0,03487
D05.SI	0,02172	0,01881		0,02364		0,02254
O39.SI	0,01932	0,01894	0,02155		0,01812	0,02312
PUBM.KL	0,01427	0,01306	0,01398	0,01390		0,01506
U11.SI	0,02122	0,01950	0,02183	0,02416	0,01867	

$CoVaR^{j\|i}_{1\%}$						
j \ *i*	BBCA.JK	BBRI.JK	D05.SI	O39.SI	PUBM.KL	U11.SI
BBCA.JK		0,04440				
BBRI.JK	0,07928					
D05.SI	0,03859	0,03381		0,03691		0,03987
O39.SI	0,03968	0,03540	0,03383		0,03568	0,03617
PUBM.KL	0,02978		0,02513			
U11.SI			0,03995	0,04081	0,03596	

$\Delta CoVaR^{j\|i}_{5\%}$						
j \ *i*	BBCA.JK	BBRI.JK	D05.SI	O39.SI	PUBM.KL	U11.SI
BBCA.JK		0,00983	0,00558	0,00632	0,00547	0,00597
BBRI.JK	0,01701		0,00829	0,00829	0,00470	0,00771
D05.SI	0,00515	0,00260		0,01202		0,01118
O39.SI	0,00420	0,00384	0,01136		0,00318	0,01320
PUBM.KL	0,00385	0,00271	0,00379	0,00468		0,00537
U11.SI	0,00461	0,00336	0,01070	0,01344	0,00241	

$\Delta CoVaR^{j\|i}_{1\%}$						
j \ *i*	BBCA.JK	BBRI.JK	D05.SI	O39.SI	PUBM.KL	U11.SI
BBCA.JK		0,01733				
BBRI.JK	0,03856					
D05.SI	0,01284	0,00459		0,01961		0,01645
O39.SI	0,01367	0,00677	0,01884		0,00963	0,02012
PUBM.KL	0,01006		0,00729			
U11.SI			0,02134	0,02456	0,01014	

Table A6- *Network-CoVaR* and *Network-ΔCoVaR*. *Notes:* This table presents the 95% and 99% confidence *Network-CoVaR* and *Network-ΔCoVaR*. The *Network-CoVaR* is estimated through the estimated banking institution i's *VaR* and quantile regression's coefficients of the entire sample of the banking institution j's daily returns on the entire sample of the banking institution i's daily returns. The *Network-ΔCoVaR* is the difference between $CoVaR^{j|i}$ and $CoVaR^{j|i(median)}$. In green we highlight the lowest *Network-ΔCoVaR* values for each institution j and in red the highest values. The blank cells represent the statistical irrelevant relationships.