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Contagion of the Global Financial Crisis and the Systemic Risk in the Banking System: Bivariate EVT Analysis in 6 Emerging Asia Economies

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Abstract

This thesis aims to study the contagion and systemic risk of the Global Financial Crisis by analyzing tail dependence between market stock returns and bank stock returns between US, Europe and selected emerging Asian economies (Indonesia, Malaysia, Thailand, Philippines, Singapore, and South Korea). We apply the concept of bivariate Extreme Value Theory to model the dependence between two returns series for each variable under examination.

We find dependencies between pairs of markets that are influenced by their size, especially for large markets in emerging Asian countries that tend to have a higher dependency to the market in the more advanced country such as the U.S. and some countries in Europe. The results also suggest that the dependencies between market returns and bank stock returns in the same region tend to be higher than dependencies between these returns across two different regions. We also find that larger institution has more dependencies with the market stock, suggesting that larger-size bank can cause disruption in the market. Further, the higher probability of extreme loss can be seen during the crisis period, which is shown by the non-linear dependency between the pre-crisis and the post-crisis period. Finally, our analysis suggests that systemic risk appears in the domestic banking systems in emerging Asia, as shown by the extreme dependencies within banks in the system. Overall, our results provide caution to policy makers and investors alike on the possible contagion of the impact of global financial crisis across different markets.

Keywords: Global Financial Crisis, Extreme Value Theory, contagion, systemic risk.

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1. Introduction

Since the Global Financial Crisis (GFC) hit the world economy in the 21st century, the issue of contagion has gained considerable attention among policymakers. More researchers and financial authorities have been looking for tools to assess, forecast and mitigate the risk posed by the rapid financial activities across the border. The interconnectedness of financial systems promotes a higher level of contagion risk across country borders through the network of financial transactions between markets and financial institutions. Crises have direct consequences to the economy by disruptions in the financial system and, in particular, the banking system.

As the most considerable part of the financial structure, banks play an essential role in the economy. The disruption in banking system causes wide spillovers to other parts of the economic systems, mainly by reducing banks' ability to provide financing in the market, which in turn lowers the economic growth.

Systemic risk in the banking sector occurs through several possible channels such as direct cross exposures in the interbank markets and credit interlinkages. It also occurs through the exposures of local banks to overseas banks, which become the source of crisis transmission to the domestic economy.

As the magnitude of such contagion shocks is likely to be amplified, and the frequency of the crisis becomes more intense, it is very important to understand the potential risks associated with increased financial integration and the development of the financial system. However, the question of whether there is a contagion crisis entering the economy and whether a financial institution caused systemic risk remains a controversial issue.

Such a case can be seen in Indonesia in 2008. The Indonesian government announced that the U.S. subprime mortgage crisis had affected the Indonesian economy. The government needed to save a failed bank, Century Bank, as the bank was deemed to pose a systemic risk to the banking system. This case generated wide public attention as the restructuring cost of this relatively small bank amounted to Rp. 6.7 trillion, which was ten times as much as the initial estimation of the restructuring cost of Rp. 632 billion. As there was no available evidence to support the assessment of the economic impact of the crisis and the determination of whether Century Bank's failure posed a systemic risk to the banking industry, the substantial increase in the cost of restructuring the bank became a national issue and caused political instability. This case shows the importance of understanding how the contagion of Global Financial Crisis impacted a domestic banking system.

This thesis focuses on six emerging economies in the Asian region: Indonesia, Thailand, Malaysia, Philippines, Singapore and South Korea. These countries are among the world's most rapidly growing economies and were also known to be profoundly affected by the Asian financial crisis in 1998.

This paper consists of three main parts. First, we analyse the dependency in the stock market between crisis origin countries and six emerging Asian economies to indicate the contagion of two world economic crises. We give further attention to the dependence on the international banking stock by observing the existence of bank channel contagion. We consider that investigating stock markets is relevant as a proxy of economic stability. Next, we detect the occurrence of the crisis in the banking system by analysing the dependencies between bank stock returns as indicators of the potential systemic risk in the banking system. We use the bivariate Extreme Value Theory (EVT) framework in our study based on the study done by Hartmann, Straetmans and de Vries (2009). Lastly, we discussed the practical implications of our findings for investors and regulators.

The result of the study can be used to identify and mitigate the spread of external risk in an economy. Furthermore, a better understanding of the potential risk of contagion will provide benefits for policymakers in designing mitigation and policy responses to tackle the potential impact of a banking crisis and to give more confidence in the country's economic and financial stability.

2. Theoretical Framework and Literature Review

This section discusses several concepts and definitions from relevant scholarly literature. A number of techniques used in previous studies to measure contagion and systemic risk are highlighted. The chapter starts by discussing the theory behind financial and banking crisis. Subsequently, the risk of contagion in a crisis and the danger of occurrence of systemic risk in the banking crisis are elaborated.

2.1 Financial Crisis

A financial crisis is a situation when a country experiences a large downturn in their financial assets value. Claessens and Kose (2013) describe a crisis as a multidimensional event that is hard to characterise using one single indicator. They describe a crisis as a sequence of substantial disruptions in financial intermediation and the supply of external financing. These disruptions are then followed by large-scale balance sheet problems of firms, households, and government. Disruptions also change credit volume and asset prices which are then followed by the need for large-scale government support in the form of liquidity support and recapitalisation. Some typical characteristics of a financial crisis are a drop in asset prices and an increase in the market volatility. These disruptions causes a decline in its output and leads to economic slowdown.

In their paper, Claessens and Kose (2013) explain four types of financial crises; currency crises, sudden stops, debt crises and banking crises. A currency crisis occurs due to a speculative attack on a currency by investors. This action causes a sharp depreciation of currency value and forces the authority to engage in devaluation policies, such as by spending the international reserves, changing interest rates, or enforcing capital controls. A currency crisis, for example, occurred when the Thailand Bath collapsed and triggered withdrawal of foreign direct investment (FDI) from the whole region in 1997-1998.

The sudden stop is a simultaneous occurrence of currency crises, marked by an abrupt reversal in the aggregate capital flows. It results in a massive current account deficit and a distortion in the balance of payment. Foreign investors' behaviour typically causes sudden stops by reducing or stopping capital inflows into an economy. Domestic residents can also trigger sudden stops when they pull their money out of a domestic economy. A sudden stop occurred in Mexico in 1994 and cost Mexican government $10 billion in government reserves and 30% decline in asset prices.

In recent years, debt crises are a major issue in the economy. A debt crisis happens when the government fails to meet their obligations, often leading to defaults. Sy (2004) defined debt crisis either as an event when there is a sovereign default or an event when secondary market bond spreads become higher than a critical threshold. This crisis is typically triggered due to government's inability to manage their source of growth.

Last, a banking crisis is the most common, but the least understood, type of crisis. Dermirgüç-Kunt and Detragiache (1998) define banking crisis as a failure in the banking system which occurs when the economy experiences both low growth and high inflation. This kind of crisis is usually indicated by significant losses in the banking system, liquidity shortage which in turn leads to bank runs by depositors. Government typically needs to intervene by liquidating banks or bailing them out. The main cause of a banking crisis can be traced to an increase in non-performing loans due to the devaluation of assets that puts pressure on the bank's balance sheet. It then leads to a devaluation of the bank's equity value.

One main challenge of studying a banking crisis is in determining the start and the end period of the crisis. Reinhart and Rogoff (2009) argue that the beginning of banking crisis can be determined by the bank runs and merging or take-over by the government.

2.2 Contagion Crisis

The broadness of the issue about contagion and how it is measured lead to different definitions of contagion. These different definitions reflect the different ways of measuring how transmission of shocks occurs. Therefore, researchers and policymakers should be careful in using the different definitions to ensure proper response can be developed to counter the unwanted consequences of a crisis to the economy.

The World Bank's definition of contagion has three different layers. First, in a broad sense, contagion refers to a general cross-country correlation. Based on this definition, countries have linkages that exist even in the absence of shocks. The second definition of contagion is more restrictive and refers to contagion as transmission of common shocks across countries beyond their fundamental linkages. This kind of contagion is about the co-movement of countries' fundamental economic indicators due to the herding behaviour of either rational or irrational investors. Finally, the most restrictive definition of contagion refers to situations when there are significant increases in cross-country correlations during a crisis period relative to a stable period. Dornbusch, Park, and Claessens (2000) extend the explanation of this type of contagion by including also the degree in which asset prices or financial flows move together relative to the co-movement in tranquil times.

2.2.1 Measuring Contagion

The method of measuring contagion again depends on which definition is used in a study. Pericoli and Sbracia (2003) summarise five representative definitions of and measurement methods for contagion as listed below:

1. *The changes in the probability of a crisis*. Contagion can be defined as the significant increase in the probability of a crisis occurring in a country given that another country experiences a crisis. One can measure the extreme change in the set of macroeconomic and financial indicators for each country to predict the probability of a crisis occurring. This kind of measurement can be used to forecast currency and banking crises.

2. *The correlation in rates of return.* One broad definition of contagion relates to a significant increase in the co-movement of prices and quantities across markets when a crisis occurred in one of the markets. Contagion can be measured by using a single-factor model with a constant variance which relates to the increase in correlation of rates of return. Co-movement in the financial market can be estimated by comparing cross-country correlations during tranquil and crisis period. Recent developments attempt to study contagion using the movement in stock returns. This method is referred to as the Extreme Value Theory (EVT). EVT offers a more robust approach to measuring the extreme movement in the equity market. Hartmann, Straetmans and de Vries (2004) use EVT to get a better understanding of the joint probability of exchange rates crash. In another study, they also use this approach to study the joint crash in stock and bond markets in the G-5 countries. Among the advantages of this method, EVT does not require precise timing of the crisis and provides a straightforward and interpretable outcome. However, this model does not account for a specific channels of transmissions.

3. *Volatility spillovers.* One widely used definition of contagion is a sharp rise in asset price volatility during periods of financial turmoil from one market to another. The multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is a popular method used to estimate this type of contagion. GARCH is a model which is used to analyse interdependencies between volatilities. This model considers some restrictions that have been mentioned in the literature, such heteroscedasticity, endogeneity, and

omitted variable bias. By using vectors of rates of return and global factors, one can calculate the covariance between two markets, and measure the effect of one country-specific shock to the volatility of the other country. Another way to test the presence of financial contagion is done by analysing cross-market correlation (King & Wadhwani, 1990). A statistically significant increase in the correlation coefficient serves as an indicator for the presence of contagion. However, this way of testing for financial contagion is prone to an upward bias as there is a base value of interdependence between these markets which may mislead and cloud the increase in the correlation coefficient during turmoil period. To solve this issue, Forbes and Rigobon (2002) use an adjusted correlation coefficient for an increase in volatility during the crisis period.

4. *The jumps between multiple equilibria*. Another definition of contagion refers to the cross-country co-movement on asset price which cannot be explained by the country's fundamental economic indicators. This kind of contagion is also known as multiple equilibria contagion. The incomplete information and investor's arbitrage behaviour lead to the spread of a crisis for a given level of fundamental indicators. The challenge in calculating this type of contagion is in the difficulty of measuring the degree of agents' uncertainty in the turmoil period. Markov-switching has been used to specify the jumps between multiple equilibria in a Markov transition matrix.

5. *The changes in the transmission mechanism.* The last widely used definition of contagion is a change in transmission channel after a shock in one market. Similar to the previous definition, this definition refers to the co-movement of prices and quantities across countries. However, contagion occurs when the country-specific shock turns into a regional or global shock. An approach called structural breaks is considered to identify the contagion.

The question of how a crisis is transmitted has stimulated studies about the risk of contagion. As the crisis and contagion become more frequent and harder to predict than before, the research in this area continues to evolve. In the next section, we review the framework to assess the risk of contagion based on the transmission channels and determine the method to measure contagion.

2.2.2 Channels and Mechanism of Contagion

The contagion literature has developed from fundamental-based contagion theory that explains the shock through finance and real channel, to multiple equilibria models that incorporate investor's behaviour. In this section, we refer to Pritsker (2001) who has constructed the linkage of contagion as below:

1. *Trade Channels***.** The fundamental-based channel explains contagion from the fundamental economic linkages across countries that affect one another (Calvo and Reinhart, 1996). The theory explains standard transmission mechanisms based on trade linkages, monetary policy, and common shocks. Pritsker (2000), and Van Rijkeghem and Wender (1999) associate the real channel of contagion to the spillover of trade links between countries. When a country goes into a crisis, its trading partner would be negatively affected, primarily through a reduction in demand. Furthermore, while a country experiences a crisis, it also experiences a depreciation in its currency, making the cost of importing products from trading partners more expensive and leading to higher domestic inflation. In the case that their rival country competes in the same market, the government will force a devaluation of the currency in an attempt to increase their competitiveness. This condition spreads the crisis from one country to another.

2. *Real Channel.* Contagion from the real channel can be explained by the Keynesian open economy model (Pritsker, 2000). Pritsker (2000) analyses the contagion of crisis based on the GDP of a country (which gives an indication on the condition of the domestic financial market), banks, GDP of other countries, and several other country-specific variables. The financial market here refers to asset price stability and the liquidity of the market. Meanwhile, country-specific variables serve as proxies of the influence of monetary and fiscal policies on GDP. He argues that the stability of a financial market stimulates aggregate business demand and investment which affect the real sectors.

   Another comprehensive study of contagion through the real channel was also done by the Bank of International Settlement (2011). In their study, they explain the real channel of contagion by a global shock in a macroeconomic variable which results in weaker economic activity. Economic slowdown leads to a reduction in revenues and profits which disturbs households' and firms' balance sheet.

3. *Financial Channels***.** The contagion channel through financial linkages can be explained from several sources. Claessens and Forbes (2004) describe financial linkages as trade, credit, foreign direct investment, and other capital flows between countries. However, the widely used definition of contagion through financial channels is the co-movement of the residuals of asset return. Pritsker (2001) studies the contagion based on financial channels by measuring return on the *i*th country's stock market index, r_i, which depends on a set of common macroeconomic factors *f* and an idiosyncratic residual component u_i.

$$r_i = \alpha_i + \beta_i f + u_i \tag{1}$$

   If the residuals from estimating equation (1) are correlated across countries, then one can interpret this as contagion or co-movement that is unexplained after controlling for fundamentals. However, if market co-movements are high both in the period of a crisis and non-crisis, one can only infer that there is a substantial economic linkage between these economies. This implies that we can consider the residuals of the correlation as a proof that markets are irrational. To anticipate the irrationality of investors in the market, regulators need to impose more sound economic policies.

   The contagion through the financial channel is closely related to *investors' arbitrage* behaviour, known as the margin-call mechanism. Investors decide to sell their asset once the price declines in a country that goes into a crisis. The arbitrage behaviour in time of a crisis might lead to a more severe contagion given that investors hold more information. This condition is also called *pure contagion,* which is defined as a crisis that is triggered by crises in other locations that is unexplained by changes in fundamental economic indicators.

4. *Bank Channel.* Contagion through bank channel happens when a bank is exposed to a financial crisis in a foreign country due to its loan portfolio. Countries that depend on a common bank are more prone to crisis than those who do not (see Kaminsky and Reinhart 2001). A crisis that occurs in a country impacts the bank's balance sheet forcing the bank to rebalance its portfolio. In their analysis, foreign banks play a significant role

in propagating the impact of a crisis as they have the power to call loans and stop credit lines. This result is in line with the findings by Caramazza, Ricci, and Salgado (1999), Kaminsky and Reinhart (2000), and Van Rijckeghem and Weder (2000) who found some cases where the impact of a crisis affects other regions, such as in the case of crisis in Mexico, Asia, and Russia.

In a weak economic condition, when confronted with a high risk of losses due to the rise of the non-performing loans, banks often need to sell their assets in other countries in an attempt to restore their capital adequacy ratios. Banks are forced to liquidate their illiquid assets to pay for their liabilities, creating an excess supply in the market. In this situation, the excess supply of assets in the market drives asset price down and leads to sizable loss. Banks' total asset and their ability to offer lending in the market are thus reduced.

The depositors' psychology during the time of crisis also plays an important role. If depositors believe that a bank will face bankruptcy, they will try to withdraw their deposit from the bank. This causes a liquidity problem and provokes a bank run. Foreign banks that are exposed to a crisis in a country with a bank run typically attempt to pay for their liabilities using their liquidity in other countries. This action may lead to a global liquidity shortage and spread the crisis to another country.

Allen and Gale (2000) study the financial contagion through interbank exposures among banks in different regions. They incorporate market structure in their analysis to provide an understanding of the microeconomic foundation during bank defaults and also to emphasise the importance of the structure of a linkage among banks in the market.

However, observing contagion through interbank activities across countries is not always feasible due to the limitation of the available data and confidentiality issues. Researchers mostly use information on within-country exposures of various European and U.S. interbank markets as their primary research context. Meanwhile, we use the movement in stock market returns as a way to assess contagion through bank channel in this thesis.

2.3 Banking Systemic Risk

The contagion of a crisis puts pressure to an economy which leads to a higher risk in the financial system of that country. Systemic risk refers to a risk that arises when an event such as market disruption or failure in one institution triggers widespread disruption to the whole financial system and eventually to the economy (Smaga, 2014). Typically, a crisis that has the potential to cause systemic failures happens in an interconnected financial system in which one institution's failure triggers the default of other institutions.

Banks are considered as the most fragile financial institutions in many economies. The failure of one bank can disrupt the payment and settlement systems and potentially spread to other financial institutions. The spreading of disruptions comes from interbank loans and exposure to a similar portfolio. However, bank failure may also happen due to losses from market shocks or due to contagion as a consequence of other banks' failure. Laeven and Valencia (2012) defined the banking crisis as systemic when the banking systems showed significant signs of distress which then required government's intervention in the initial period of the crisis.

De Bandt and Hartmann (2000) define a systemic event from two different perspectives. The first concept is called the "closer concept" or the "domino effect". This concept refers to a crash of the financial market due to the release of bad news about a financial institution, which leads to subsequent effects on other financial institutions or markets. The broader concept defines systemic as simultaneous adverse effects on a large number of institutions or markets as a consequence of severe and widespread shocks. Schwarcz (2008) sums up all definitions of systemic risk in the literature by emphasising that all definitions are always associated with a trigger event, which may have different forms such as an economic shock, or failure of an institution. These disruptions in the banking system result in adverse economic consequences.

There are several causes of a systemic crisis. The first comes from the fact that banks are linked to one another by interbank deposit market, syndicated loans, and interest rate deposit (de Vries, 2003). Dragan et al. (2013) suggest that mismanagement of credit risk is a notable trigger of a systemic crisis. This problem arose when banks failed to calculate their risk portfolio and liquidity requirements based on their credit exposures. A systemic crisis can also come from the macroeconomic shocks that impact the banking system. For instance, when there is a significant adjustment in the interest rates, there will be a rise in the banks' costs. In this case, banks are forced to bear the higher cost of financing, which may follow by worsening the quality of the loan portfolio. When this situation emerges in quite a long period, banks could eventually experience a capital shortage.

In the next session, we discuss the channel, mechanism and several methodologies to measure systemic risk in the banking system.

2.3.1 Channels and Mechanism of Banking Systemic Risk

Previous literature that discussed the impact of the global financial crisis on the banking system so far focused on the banking in the American and European contexts. These regions were often the most affected by the GFC due to the international operations of their banks. Differently, in emerging economies, banks are still focused on their domestic operations. However, this does not mean that banks in emerging economies are adequately protected from an adverse macroeconomic shock that might reduce their assets value. Moreover, distress or a failure in one bank might still affect other banks via several channels and mechanisms as summarised below:

1. *Borrower balance sheet channel.* First, this explanation assumes that lenders are unable to fully assess borrowers' financial conditions, such as their risks and solvency, and unable to adequately monitor borrowers' activities or to enforce repayment of debts. We also assume that the borrowers are highly dependent on banks for credit. When the supply of bank loans declines due to a problem faced by the bank in time of crisis, these borrowers are massively impacted. Any shock in the economy will then be propagated to the real sectors. This condition further reduces borrowers' ability to repay their debt and prevents them from obtaining new financing, thus amplifying the fluctuation. Moreover, any shock in the financial sector, such as in the form of fluctuation in asset prices, also affects borrowers' net worth.
2. *Bank balance sheet channel*. There are two ways that shocks can influence a bank's balance sheet: the traditional bank lending channels and the bank capital channels. Banks often have exposure to a common portfolio in their balance sheets. Any shock that worsens banks' liquidity condition will eventually affect banks' capital. This situation could then reduce their ability to provide credits in a market and decrease the volume of

loans that the borrowers can acquire. This condition may further lead to a deterioration of the overall economic conditions.

3. *Liquidity channel*. This channel refers to a liquidity problem experienced by a bank given any shock that worsens its liquidity. This liquidity problem can quickly turn into insolvency. Once financial distress has emerged, banks will become more likely to take precautionary moves to control their liquidity. Banks may even resort to freezing their liquidity, and this will amplify the effect of a shock.
4. *Direct cross-exposure in interbank markets.* High interbank borrowing increases the scope of the risk transmission through direct debt linkages. When a particular bank is hit by a shock, it may not be able to repay its interbank debts. This will then expose other banks that provide the interbank loans. Depending on the size of interbank loans, these can cause turbulence to the overall banking sectors.

2.3.2 Measuring Systemic Risk

Cerutti, Claessens and McGuire (2012), divide the methodology to measure systemic risk on banking system based on the data requirement. In the first category, systemic risk can be approximated based on the process of the contagion based on balance sheet channels. The size of the shocks and how they amplify and propagate across borders are considered. This method requires individual-level data, which often is considered as confidential and private information.

In the second category, the systemic risk of shocks across different markets is investigated based on publicly available information, such as stock price, asset price, credit spreads, and other market data. This method assumes that these prices reflect all information of publicly traded firms.

Furthermore, the approaches to measure systemic risk can be categorized into two different types: the top-down and bottom-up approach. We discuss these two approaches in the following subsections.

Bottom-Up Approach

The bottom-up approach is primarily used to capture the contribution of a single institution to the systemic risk. In particular, this framework describes the relation between individual distress to the whole system. Several prominent methods to measure the systemic risk that are based on institutional level approach are ΔCoVaR, MES (Marginal Expected Shortfall), SRISK (Systemic Risk Measure), and joint Probability of Distress (DIP).

Adrian and Brunnermeier (2010) first introduced CoVaR to investigate the institutional contribution to systemic risk based on the Value at Risk (VaR) and market data. The term *CoVaR* consists of two parts, where the first part, "Co", stands for co-movement, or conditional, and the second part, "*VaR*", represents the risk faced by a particular institution. *VaR* is the maximum loss which might happen in an institution with a certain level of probability conditional on the fact that the institution is under distress. The value of *CoVaR* for a given bank represents the contribution of a given bank to the potential systemic risk that might be faced by the financial system in a distress situation. The idea behind this method is that the financial health of an institution affects the distribution of asset values and the health of the financial system. When a financial institution experiences stress, it will affect the whole system. The *CoVaR* estimates the size of the tail of the distribution of asset values in the system and the change after an institution experienced distress. The low and negative CoVaR value represents the risk of a bank to the financial system. Calculation based on CoVaR method considers several institutional characteristics, such as leverage, size, and maturity mismatch, to predict the contribution of a particular institution to the systemic risk faced by the overall financial system.

The CoVAR was initially used to assess the spillover of risk between two institutions, and it is difficult to generalise its result in the context of systemic risk (Zhou, 2010). The difficulty in applying this method is due to the fact that it is necessary to construct a system indicator to assess the risk in the system and then further analyse the relationship within the system. Furthermore, another drawback of this method is that it cannot measure the potential risk outside the range of probabilities that are chosen. Previous literature turns to the Expected Shortfall method of calculating a potential systemic risk to account for the shortcoming of CoVaR. Expected Shortfall is calculated as the average expected return of the market that exceeds certain confidence level that was first employed by VaR.

Acharya, Pedersen, Philippon and Richardson (2010) introduced Systemic Expected Shortfall (SES) to measure firm's contribution to systemic risk by accounting for the institution's leverage and expected loss. This method is believed to have a good predictive power during a financial crisis. Later, they extended SES by introducing Marginal Expected Shortfall (MES) as a method to forecast SES in a crisis. The MES is proportional to the systemic risk and the coefficient corresponds to the expected shortfall in the market return. Previous work by Adrian and Brunnermeier (2011) show that conditional VaR and $\Delta CoVaR$ on the market value of asset returns give results that are similar to SES or MES. The results of these methods also provide an estimation of the amount of capital needed in the period of crisis.

Another method to measure the contribution of a financial institution condition to the systemic risk is SRISK. Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012) extend the use of MES by incorporating macro-finance analysis to measure the conditional firm's expected capital shortfall due to a severe market decline. SRISK captures the expected capital shortage of an institution based on its size, leverage, and risk. This method allows one to rank financial institutions in different stages of a crisis. The risk is measured based on the co-movements of firm's equity.

Another development in the study of a systemic risk that is based on the interconnectedness within the system is known as the network analysis. This approach focuses on the connection between banks and the strength of the link between them. However, this method requires bank-level data (financial statement) in combination with aggregate country level cross-border exposure data which is hard to obtain. The balance-sheet network analysis is believed to provide a better insight to evaluating a systemic risk arising from the interconnectedness of financial institutions than other methods.

The modern statistical instrument that we adopt in this thesis is called Extreme Value Theory (EVT) and is known for its application in estimating the extremal dependence on financial stock returns. Recent progress on this study on multivariate EVT provides more insight to investigate co-movements between asset returns. The basic idea behind this method is that an institution that is prone to risk has asset returns which exhibits fatter tails than the normal distribution. The systemic risk arises when the extreme probability of loss links to another institution. With the multivariate EVT, the interconnectedness of crises is approximated from the linkage of their tails.

Table 1. Institution Level Systemic Risk Models

	Conditional Value-at Risk (CoVaR)	Conditional Risk (CoRisk)	SRISK	Systemic Expected Shorfall (SES)	Distress Insurance Premium (DIP)	Joint Probability of Default (JPoD)	Systemic Contingent Claims Analysis (CCA)
Systemic Risk Measure	Value-at-Risk	Value-at-Risk	Expected Shortfall	Expected Shortfall	Expected Shortfall	Conditional Probabilities	Expected Shortfall
Conditionality	Percentile of Individual Return	Percentile of Joint Default Risk	Threshold of Capital Adequacy	Threshold of Capital Adequacy	Percentage threshold of system return	Various (individual or joint expected losses)	
Dimensionality	Multivariate	Bivariate	Bivariate	Bivariate	Bivariate	Multivariate	Multivariate
Dependence Measure	Linear, parametric	Linear, parametric	Parametric	Empirical	Parametric	Non-Linear, Non-Parametric	Non-Linear, Non-Parametric
Method	Panel Quantile Regression	Bivariate Quantile Regression	Dynamic Conditional Correlation (DCC GARCH) and Monte Carlo simulation	Empirical Sampling and Scaling; Gaussian and Power Law	Dynamic Conditional Correlation (DCC GARCH) and Monte Carlo Simulation	Empirical Copula	Empirical Copula
Data Source	Equity Prices and Balance Sheet Information	CDS Spreads	Equity Prices and Balance Sheet Information	Equity Prices and Balance Sheet Information	Equity Prices and CDS Spreads	CDS Spreads	Equity Prices and Balance Sheeet Information
Data Input	Quasi-Asset Returns	CDS Implied Default	Quasi-Asset Returns	Quasi-Asset Returns	Equity Returs and CDS-Implied Default Probabilities	CDS-implied default probabilities	Expected losses ("Implicit put Option")
Reference	Adrian and Brunnermeier (2008)	Chan-Lau (2010)	Brownlees and Engle (2011)	Acharya and others (2009, 2010 and 2012)	Huang and others (2009 and 2010)	Segoviano and Goodhart (2009)	Gray and Jobst (2010 and 2011)

Source: Jobst and Gray (2013)

Top-down Approach

Assessing banking system stability through the bottom up approach usually relies on balance sheet level data. However, an interbank relationship, which is one of the most critical data to assess systemic phenomena, is particularly hard to measure and monitor (Hartmann, Straetmans, and de Vries, 2005). The top-down framework aims to identify the connection of the macroeconomic shock to the financial sector and real economy. This method is typically done by constructing the historical behaviour of time series data to evaluate the previous systemic risk event.

In the literature, a macro-financial stress test is employed to quantify the link between macroeconomic variables and financial institutions in the financial system. This method provides a forward-looking perspective to get a better understanding of how a shock may escalate to a severe systemic event. The Central Bank in some countries used the macro-financial stress test to measure the resilience of the financial system to various stress situations. Early studies on stress test used complex equations to link aggregate profits and losses to macro developments (e.g. Blaschke et al. (2001) or Bunn et al. (2005)).

The most recent method for assessing systemic risk is RAMSI, which was developed by the Bank of England as its risk assessment model (Aikman et al., 2009). This model allows one to capture counterparty credit risk in the interbank market and allows for feedback channels that arise from market and liquidity risks. Due to the data limitation for estimating these equations econometrically, liquidity risk is modelled by a range of indicators that change during the time of stress and is calibrated to past crises (Kapadia et al. (2011).

By accounting for macroeconomic shocks, Jacobson et al. (2005) use a reduced-form approach to assess the systemic risk in the Swedish banking system. They developed a model linking macroeconomic factors and balance sheet specific factors to the default of financial institutions. They used a module tracing the evolution of balance sheets in response to macroeconomic factors by Vector Autoregressive model (VAR). However, their model needs specific data and explicit scenarios of how shocks translate into losses to produce a reliable result.

2.4 Brief Synopsis of Earlier Work

Academic literature on financial crisis and contagion provides empirical evidence concerning causes and propagation mechanisms of contagions. This section delves into past literature of financial and banking crisis, contagion risk, and the systemic risk during a crisis. In this thesis, we focus on the period which involves two recent crises, the U.S. subprime mortgage and European sovereign crises, and their implications on the emerging Asian countries.

2.4.1 Recent Economic and Financial Crisis

Recent financial crises provide opportunities to analyse factors, characteristics, and transmission mechanisms of a crisis. As a crisis tends to evolve over time, it gives a picture of the potential ways to mitigate a similar crisis in the future. In the early 21st century, the world experienced two major crises. The first one is known as the U.S. subprime mortgage crisis and the second is the Eurozone sovereign crisis. Together, the high magnitude of these two crises resulted in a distortion in stock and credit markets, as well as in the real sectors.

The Global Financial Crisis first started due to the subprime mortgage problems in the U.S. The fundamental cause of the default was the high exposure to the subprime market. The U.S. housing prices started to increase from 1996 to 2006, which became a bubble in the housing market. At that time, the market provided various loan incentives including interest repayment terms, low initial teaser rates, and refinancing facilities to attract borrowers. Hassan (2013) mentioned three fundamental sources of the U.S. financial bubble: 1) excessive risk-taking behaviour and excessive leveraging from the U.S. financial institutions, 2) complex mortgage derivative products, inadequate enforcement by regulatory agencies, and processes that encourage moral hazards and reckless speculations, 3) the failure of market and government institutions.

The housing prices started to decrease slowly from 2006 to 2007 due to the difficulties in the refinancing scheme. The high default rates on the subprime sector finally caused the bubble to burst. Major Banks and financial institutions around the world reported a total loss of approximately USD 379 billion by May 2008. The bankruptcy of Lehman Brothers marked the peak of the crisis on 15th September 2008

The subprime mortgage crisis in 2007 caused severe damages to businesses, stock markets, and the U.S. economy. The problem also spread to the global financial market. Since then, the repercussions of the U.S. subprime mortgage crisis and the way it transmitted to other countries has become a major interest in many studies.

Previous studies show how crisis in one country can cause a significant impact on the global economy as it is transmitted via several channels. Wynne and Kersting (2009) reported that due to the U.S. subprime mortgage crisis the world trade declined by 32%, more than two times as much as the 15% decline in trade due to the Great Depression. In another study, Lee (2012) investigated the occurrence of contagion based on the correlation coefficients between the U.S. stock returns and 20 other international stock returns in developed and emerging markets. He found that stock returns in Hong Kong, Taiwan, Australia, and New Zealand were affected by contagion.

Yılmaz (2010) inspected the extent of contagion and interdependence across the East Asian equity markets during the global financial crisis and found evidence of direct linkage in returns and volatility between these equity markets.

Cheung et al. (2010) found evidence of contagion in their analysis of market interdependence and credit risk spillover effects of the 2007–2009 global financial crisis in various countries such as the UK, Hong Kong, Japan, Australia, Russia, and China. In another study, using multivariate GARCH, Dimitriou and Simos (2013) found empirical evidence of contagion of the U.S. subprime mortgage crisis in equity markets in the European Monetary Union, China, and Japan.

The impact of the U.S. financial crisis in 2008 spread to the global economy and turned into a global crisis. When the world's economy had not fully recovered from the U.S. subprime mortgage crisis, it faced another shock from European countries. The crisis was triggered by the high level of debts in the region which had accumulated over the years. The announcement of the distressed level of the sovereign debt from the Greek government in late 2009 marked the beginning of the crisis. At that time, the debt position of the Greek economy reached 300 billion Euro and the budget deficit amounted to four times the level allowed by the Maastricht Treaty.

In May 2010, Greece's financial problems worsened, and this caused extensive attention to the macroeconomic and fiscal imbalances in the European Economic and Monetary Union (EMU), especially in countries with high sovereign debts such as Portugal, Italy, and Spain. The fear of contagion increased as there were concerns regarding the exposure of banks in the European Union to the Greek economy. Since May 2010, the European Union has bailed out Greece, Ireland, Portugal, and Cyprus. The sovereign debt problem has affected Eurozone countries and their trading partners and stockholders across the world. The crisis was followed by an increase in yield for bonds owned by several countries within the Eurozone.

Several studies observed how the magnitude of the U.S. subprime mortgage and Eurozone sovereign crises caused spillover effects to the world's economy through two primary channels: trade and financial market. The impact of the crisis spread through the trade channel due to the drop in demand by these countries in the period of crisis, which in turn impacted their trading partners. Furthermore, several institutions revised the world economic growth from an increase of 2.2% to a decrease of 1.8% in 2009[1]. This decline was considered as the most substantial contraction after World War II.

Dungey and Gajurel (2013) found substantial evidence of the effects of contagion from the U.S. equity market to several emerging markets in Asia. While the U.S. suffered the subprime mortgage crisis, emerging Asian countries were also hit, as can be seen by indicators such as the average drop in the stock market index by 17%. Singapore's stock market experienced the highest drop (-27%), followed by Thailand's (-21%) and the Philippines' stock market (-21%)[2]. They also observed the connection between contagion and the potential of systemic risk for banks in the crisis period. They found that the shock transmission via idiosyncratic contagion significantly increases the likelihood of occurrence of a systemic crisis in 53 domestic banking systems. Furthermore, they also found that banking sectors across the world were disturbed by the crisis and were not immune to contagion. There were at least 18 banking systems that also experienced a crisis during the Global Financial Crisis.

Tabarraei (2013) presented some evidence that banks in advanced economies have contributed to the spread of the Euro-crisis to the emerging countries. By using data on international banking flows, he assessed lenders' channels and found the impact of the Euro-crisis on emerging countries around the world including Asian countries via multinational banks.

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[1] See Claessens and Kose (2013).
[2] Source: Anderson (2009), UBS

Aizenmann et al. (2012) analyzed the vulnerabilities of emerging countries that faced shock due to crisis in advanced economies. By assessing the effect of news from the countries where the crisis originated, they found a limited impact of the shock to equity returns and bond markets in developing countries.

Fratzscher et al. (2011) observed the global transmission of the impact of the crisis in the U.S. market in the period between 2007 and 2009 to the equity-portfolio in 55 countries. They found a systematic but small effect of contagion in the global financial sector from their analysis of the asset pricing. However, they found that country-specific factors such as fundamental economic indicators and domestic policies substantially affected the market and investors' behaviour. Meanwhile, Forbes and Rigobon (2002) found that the movement in one stock market has an impact on any other markets across the world regardless of their size and structure. They found the evidence of a crash in the U.S. market index and its effect on major stock markets around the world.

Karolyi (2003) studied several possible channels of contagion, ranging from co-movement of asset price, market volatility, and capital flow. He emphasised the relationship between asset returns and capital flow and argued that this is pertinent to uncover the presence of contagion. However, he noted that even though previous studies have focused on the extreme asset returns as a statistical approach to model contagion, most of these studies did not control for fundamental economic indicators.

2.4.2 Systemic Banking Crisis

There were numerous cases of high-profile banking crises in previous literature, among them are the cases in Mexico, East Asia, Scandinavian countries, Argentina, and the Asian Financial Crisis. These crises were mainly characterised by extensive defaults in the banking system which led to an economic recession.

Based on Laeven and Valencia (2012) the cost of banking crises varies across dimensions from the fiscal costs, output loss to increases in debt. In the Asian Financial Crisis, for example, Indonesia experienced 57% fiscal cost to GDP, 68% increase in debt and Thailand experienced 109% output loss in percent of GDP. The crisis began in Thailand in July 1997 and quickly spread to Malaysia, Indonesia, Korea, and the Philippines. Surprisingly Singapore, a relatively advanced country which became a regional financial hub with an open economy in this region, was also affected.

Recently, Cetorelli and Goldberg (2011) investigated the impact of liquidity shocks in the banking systems on emerging countries' economic conditions. By examining bank-level data, they found that the transmission of the impact of a crisis emerged through the contraction in the supply of loans, both from local lending by foreign banks affiliates in emerging markets and from cross-border lending by foreign banks.

In another study by Hartmann, Straetmans and de Vries (2004), EVT was applied to measure contagion risk from banking stock market across borders. Their result suggested that there was a weak but significant spillover effect to banks in the Eurozone as well as a potential systemic risk across the border from the US.

3. Literature Gaps and Research Questions

This study aims to fill a gap in the current literature by studying the contagion from the dependency between market returns in advanced economies, such as the U.S. and Europe, and emerging Asian economies. We investigate the dependency of the market and bank stock returns to find an indication as to whether banks serve as a channel of contagion for a crisis in the economy. As well as the dependency between bank stock returns to find an indication of the presence of systemic risk in the banking system. Therefore, this research aims to pursue the following themes: 1) this research explores the contagion of the recent Global Financial Crisis from the U.S. subprime mortgage and Euro sovereign crises to five emerging Asian economies, and 2) this research explores how the systemic risk in the banking system of these countries.

To our knowledge, there are limited studies that use market interdependency as a framework to investigate the contagion effect of the Global Financial Crisis to the emerging Asian countries. Furthermore, the literature that directly investigates the impact of the crisis on the banking system is also scarce. Therefore, this thesis attempts to contribute to the body of knowledge by using a different approach to study contagion and the systemic risk in the banking system in the relatively less-studied context of the emerging Asian countries.

The research questions in this thesis are:

(1) Is there any contagion effect of the U.S. subprime mortgage and Europe sovereign crises to the Asian emerging economies?
(2) Are banking systems in these countries exposed to the systemic risk during the crisis period?

To answer these questions, we developed two hypotheses:

H1: There is a strong dependency between the U.S., European, and Asian stock markets that indicate the contagion of the Global Financial Crisis

H2: There is a strong dependency on bank stock returns in the emerging Asian banking systems which serve as an indication of the systemic risk in these countries.

4. Research Design

In this section, we explain the empirical method to examine the contagion risk of the recent Global Financial Crisis to the Asian emerging economies. We refer to the study conducted by Hartmann, Straetmans and de Vries et al. (2009) by modifying the object of analysis from exchange rate returns to the market and bank stocks returns.

4.1 Methodology

The shape of the tail of a financial distribution is one of the primary methods to learn about the financial risk. The study of the tail of asset return distributions in the financial literature can indicate the probability of a market crash. The common findings in many economic articles suggest that the distribution of asset returns exhibit fat tails, implying that the probability of extreme events is higher than studies based on a normal distribution. Assuming that asset returns are normally distributed underestimates the probability of a crisis and the impact of the event.

Stock markets often show an extreme dependence, which is defined as the dependence between extreme large returns. This extreme dependence does not exist in tranquil periods but generally emerges during crisis periods, which are characterised by crashes in stock markets. Nevertheless, one can detect the extreme dependence in the data in tranquil periods. During turmoil periods, the dependence between markets is much stronger relative to tranquil periods. During crisis periods, a crash in one market can easily propagate to other markets which we consider and label as contagion. Therefore, understanding the tail dependency is useful in predicting the probability of contagion.

The joint occurrence of extreme returns in different markets is called co-exceedance. Co-exceedances in different markets can be assessed by measuring the asymptotic tail dependence based on the conditional probability that one variable exhibits extreme values given the other variable. The existence of contagion can be explored from fundamental economic linkages across countries such as trade linkages, monetary policy, and common shocks (Calvo and Reinhart, 1996). However, according to Dornbusch et al. (2000), contagion could also be a result of "irrational" behaviour due to loss of confidence and herding behaviour.

Among the methodologies to model extreme dependence and measure the tail risk, the method we consider in this thesis is the Extreme Value Theory (EVT). This method is an approach to capture the tail-behaviour of multivariate stock returns. We use the logarithm of nominal bilateral market stock return to measure the extreme dependency between stock returns. The extreme dependencies between markets which we consider as the crisis-origin countries and the emerging Asian countries represent the contagion between these markets. Later, we also assess the dependency between the stock market and bank stocks returns, to indicate the contagion from the bank channel. Finally, we estimate the systemic risk in the banking system by measuring the dependency between bank stocks returns. As suggested by Schoenmaker et al. (2005), systemic risk can be defined as the extreme dependency on the tail distributions of bank stocks returns.

4.1.1 Heavy Tails

One of the prominent stylized facts of financial returns is that they follow non-normal distributions. This implies that the financial log returns decay slowly. Let F(x) denote the distribution function of financial variable X_i. This variable is a financial return. Suppose returns are independent and identically distributed. Variable X_i is said to exhibit a heavy tail distribution with power-law type when the tail of distribution converges to Pareto:

$$F(x) = 1 - x^{-\alpha}\, L(x) \quad \text{as } \alpha > 0,\ x \rightarrow \infty \tag{2}$$

Where the function *L(x)* is such that for any *x>0:*

$$\lim_{t \to \infty} \frac{L(tx)}{L(t)} = 1 \tag{3}$$

There are two parts of this tail distribution, the *L(x)* function and the power part. Since the *L(x)* function is slowly varying at infinity, we can neglect this part. We assume further that *L(x)* is constant. We focus on explaining the power part of $x^{-\alpha}$, where α is the tail index. The tail index equals to the number of bounded moments. A larger value of α indicates the less extreme behaviour of the returns. An example of a distribution which converges to Pareto is the Student-T distribution.

The power part of the tail function *F(x)* makes that this function falls off more slowly than the exponential type of distribution such as the normal or log-normal distribution. As we discussed earlier, most of the financial data exhibit heavy tails.

Recall that from (2), the distribution function of the Pareto distribution is

$$\bar{F}(x) = 1 - F(X) = \frac{1}{x^{\alpha}} \tag{4}$$

Where $\bar{F}(x) = 1 - F(x) = P(X > x)$ is the cumulative distribution function. The density function is

$$f(x) = \frac{dF(x)}{dx} = \alpha x^{-\alpha-1} \tag{5}$$

Another important feature of the heavy-tailed distribution is the existence of moments. The *F(x)* distribution has moments which are not always finite:

$$\int_0^{\infty} x^m \, F(dx) = \infty \tag{6}$$

The number of finite moments in a distribution indicates the thickness of its tail. We can describe the m^{th} moment of the *F(x)* distribution as:

$$For\ m \neq \alpha: E[x^m] = \int_1^{\infty} x^m f(x) dx = \int_1^{\infty} \alpha x^{m-\alpha-1}\, dx = \frac{\alpha}{m-\alpha} x^{m-\alpha} \,|_1^{\infty} \begin{cases} \infty \quad , & m > \alpha \\ \dfrac{\alpha}{\alpha - m}, & m < \alpha \end{cases} \tag{7}$$

$$For\ m = \alpha: E[x^m] = \int_1^{\infty} \alpha x^{-1} dx = \alpha \ln x \,|_1^{\infty} = \infty \tag{8}$$

Notice that the parameter α governs the tail behaviour of the distribution function. If $m \geq \alpha$, the moment m is not well defined, because it goes to infinity. When $m < \alpha$, the moment is well defined.

Before we start the analysis, we need to observe the shape of the distribution as the appropriate condition for the estimation. In this thesis, we indicate the shape of the tail by considering the summary statistics: mean, variance, skewness, kurtosis, and Jarque-bera. The non-normal distribution can be detected for example by the negative co-skewness, high kurtosis ($\kappa > 3$) and significant Jarque-Bera test statistics.

The fact that financial data exhibit non-normal distributions implies a high likelihood of extreme values in the tail of the distribution. The Extreme Value Theory is a statistical approach, which provides a framework to capture the occurrence of extreme events in the asset return distribution which is considered as probabilistic of extreme losses. This model formalises the probability of extreme loss returns in a particular function.

In this thesis, we use bivariate EVT technique to observe the joint behaviour (or 'co-exceedances') between two markets and stock returns through the analysis of extreme negative co-movements in the tail distribution. We associate the co-movement with the probability of a similar event in another market. The bivariate EVT approach makes it possible to find the risk of contagion of one institution to another institution in the system.

4.1.3 Extreme Dependencies

In our analysis, we concentrate solely on pairs of institutions and measure their conditional probability of failing given that one of the two institutions in the pair experiences a crash. The most common method to measure dependency is the Pearson coefficient of correlation (ρ). The Pearson correlation coefficient, ρ, for two random variables X and Y is defined as the covariance divided by the product of the standard deviations:

$$\rho = \frac{Cov\ (X, Y)}{\sqrt{Var\ (X).Var(Y)}} \tag{9}$$

Several advantages of using correlation coefficient to describe dependency between two variables can be attributed to its simplicity both in its application and interpretation. There are extensive works in the literature that explain the link between theory and empirical results using correlations. However, according to Forbes and Rigobon (2011), this measure is rather unreliable as a way to measure the tail dependency between two variables, especially when applied to a heavy-tailed data set. Pearson correlation coefficient cannot properly explain the volatility of the dependency between two variables during the bear and bull market conditions. Therefore, this measurement is considered biased and spurious in volatile periods.

Contrary to standard correlation analysis, which focuses on observations around the average value, the EVT measure only deals with observations located in the tails of the distribution (De Vries, 2005). In the bivariate EVT, the dependence between two extreme variables can be expressed by means of a dependence function.

Let X and Y be random returns from two risk factors. The X and Y are on a common scale, events of the form $\{X > u\}$ and $\{Y > u\}$, where for large values of threshold u, correspond to equally extreme events for each variable. When (X, Y) are perfectly dependent, then $Pr(X > u|Y > u) = 1$. This means that the impact of one extreme event implies the high probability of an extreme event in the other variable. A less extreme case is when $Pr(X > u|Y > u) > 0$, but less than 1. In other words, when X and Y stand for market stock returns and u is the common high loss, given that $Y > u$, it is also likely that $X > u$, but it is not a certainty. In case that X and Y are heavy-tailed, one typically finds that $Pr(X > u|Y > u) > 0$. However, in the case of the normal distribution, one gets $Pr(X > u|Y > u) \rightarrow 0$, even if $\rho \neq 0$. So there can be dependency in the center, since $\rho \neq 0$, which evaporates in the tails as $Pr(X>u|Y>u) \rightarrow 0$.

Following Hartmans, Straetmans, and de Vries (2009), the tail dependence or linkages measure between two risk factors is a measure of this extreme dependency:

$$E\{k|k \geq 1\} = \frac{P(X > u) + P(Y > u)}{1 - P(X \leq u, Y \leq u)} = 1 + \frac{P(X > u, Y > u)}{1 - P(X \leq u, Y \leq u)} \tag{10}$$

Which equals to

$$E\{k|k > 1\} = 1 + \frac{\#\,\mathrm{Min(X,Y)} > \mathrm{u}}{\#\,\mathrm{Max(X,Y)} > \mathrm{u}} \tag{11}$$

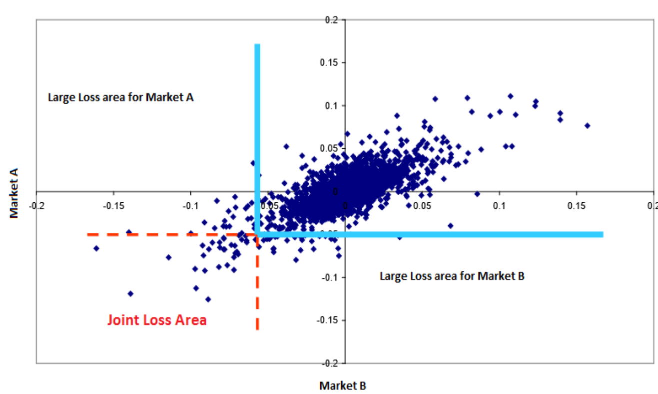
The numerator is the probability that both entities are above the threshold (u) simultaneously. The denominator represents the probability of at least one entity fails. $E\{k|k \geq 1\}$ then gives the conditional expectation measure of the other market crashing, given that one market crash. This measure is also called the extreme linkage estimator, which represents the extreme dependence of a bivariate distribution. This value ranges between 0 and 1. When the coefficient is equal to 1, the pair of variables shows complete tail dependency. When the bivariate setting show complete tail dependency, the probability that X & Y are in crisis given that either X or Y is in crisis is 1. This means that given X is in crisis, Y also experiences a crisis for sure. When the probability is between 0 and 1, for example, 0.5, the probability of X in crisis given Y is in crisis is 50%. In contrast, the 0 value of dependence coefficient represents tail independency.

The linkage estimator in formula (10) gives us the formal method to measure the dependency in the tail distribution of asset returns. Empirically we use (11) to measure (10). The measure (11) is a simple counting measure, that counts how many realizations are in the joint systemic risk area defined by the threshold *u*, divided by the number of extreme realizations by X or Y or both. Next, to give a better understanding of the Bivariate Extreme Dependence, we explain the application of this method in simulation and real data of financial returns.

4.1.4 Application of Bivariate Extreme Dependence

A simple method to observe the dependency in the tails in the bivariate EVT method is through the visual observation of a financial return scatter plots as we use in this thesis. In the visual observation, the tail dependence is indicated by the asymptotic dependence of the scatter plot. According to Schoenmaker et al. (2005), the dependency in the tail of the return distribution is indicated by the diagonal line of the plot of financial returns data. This dependency represents the sign of contagion risk between the two risk factors.

Figure 1. Contagion Measure between Markets

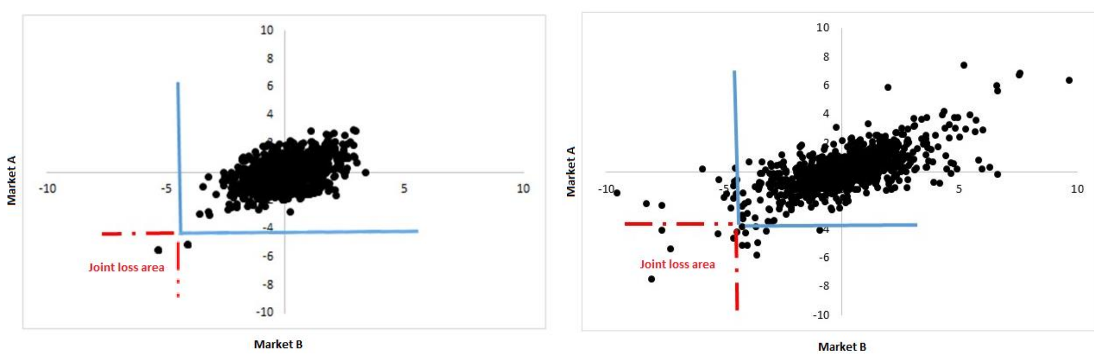


Source: Lecture notes given by Prof. de Vries at the Erasmus School of Economics (2016)

The concept of tail dependence refers to the amount of dependency in the upper-right quadrant or lower-left quadrant of a bivariate distribution. This notion is relevant to the concept of extreme values. Moreover, we are particularly interested in the dependency in the extreme negative value which is located in the lower-left quadrant. This also known as the downside risk of financial returns, which represents the occurrence of contagion. The intuition of lower tail dependency is the probability that one variable takes an extremely large negative value, given that the other variable has an extremely large negative value. So for example when one market experience an extreme loss, there is probability that the other market also experience loss. Hence, the lower tail dependence is a very important measure of dependence in the contagion literature.

When the bivariate variables have normal distributed returns, the shape of the scatter plot does not exhibit many outliers and does not form a diagonal line. In this case, most of the observations are located at the centre of the distribution, and we cannot infer that there is a dependency on the tail distribution.

Figure 2. (a) Simulated Normal Returns Distribution (b) Simulated Student-T Returns Distribution



Source: Author’s simulation using E-views program

To illustrate this, we present two simulations of random data in normal distribution and Student-t distribution. For the pair of normal distribution data, we generate a pair of 1,000 series with mean 0 and variance 1. For the pair of Student-t distribution data, we generate a pair of 1,000 series with mean 0 and 3 degrees of freedom. We define these numbers as market returns in Market A and Market B.

Figure 2 above shows the scatter plots of the simulated random normal distribution of bivariate financial returns (a) and simulated random Student-t distribution of bivariate financial returns (b). Even though both data show a diagonal line, the scatter plot of the bivariate normal distribution in the Figure 2 (a) does not exhibit many outliers relative to the Student-t distribution in the Figure 2 (b). In the simulated scatter plot above, the normal distribution displays an ellipse shape with few outliers in the tail of quadrant. Contrary to the first figure, the Student-t distribution data in the Figure 2 (b) shows more outliers in the upper and lower quadrant. Based on the study by Schoenmaker et al. (2005), the dependency at the extreme negative values as we observed in Figure 2 (b) indicates the occurrence of contagion risk.

The scatter plot of financial returns as shown in Figure 2 gives us a first indication of the extreme dependency in the data. Thus, not only by using the scatter plot, in this thesis we also use a more formal method based on the tail dependence estimator $E\{k|k \geq 1\}-1$ in formula (10). This methodology offers a way to give a precise measure for the strength of tail dependency.

To gain insight into the linkage estimator from formula (10), we conduct a small simulation experiment. We generate 20 random data pairs of variables X and Y which are normally distributed with mean 0 and variance 1. First, we take the minimum and maximum value of the two variables per pair. Then we set up thresholds from the order statistics of the mean of X and Y series. Column A gives the number of minimum values of variable X and Y which exceed threshold u that has been arranged by descending order (*#Min*[X,Y] > u). Column B gives the number of maximum values of variable X and Y which exceed threshold u (*#Max*[X,Y] > u). Finally, we take the ratio of A to B, which makes the tail dependence estimator $E\{k|k \geq 1\}-1$ from formula (11).

$$E\{k|k > 1\} = 1 + \frac{\#\ \mathrm{Min(X,Y)}\ >\ \mathrm{u}}{\#\ \mathrm{Max(X,Y)}\ >\ \mathrm{u}} \tag{11}$$

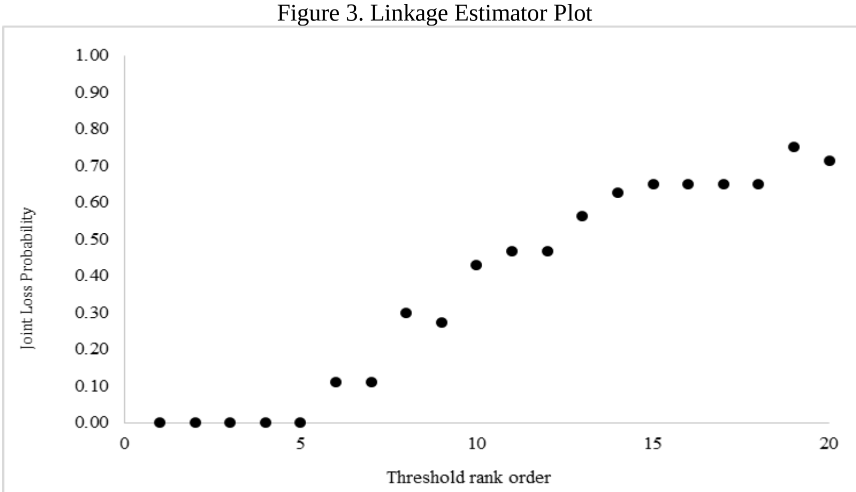
Table 2. Simulated Data for Linkage Estimator

X	Y	MIN	MAX	MEAN	THRESHOLD	A	B	RATIO
		-0.645	-0.352	-0.498	1.172	0	8	0.000
-0.352	-0.645	-1.624	-0.668	-1.146	1.097	0	8	0.000
-1.624	-0.668	-1.925	1.408	-0.258	1.056	0	8	0.000
1.408	-1.925	-0.303	0.446	0.072	0.919	0	8	0.000
-0.303	0.446	-1.830	0.551	-0.639	0.601	2	9	0.222
-1.830	0.551	-0.475	-0.271	-0.373	0.531	2	10	0.200
-0.271	-0.475	-0.951	1.234	0.141	0.141	4	13	0.308
-0.951	1.234	-0.819	-0.800	-0.810	0.072	4	13	0.308
-0.800	-0.819	-0.529	1.591	0.531	0.047	4	13	0.308
1.591	-0.529	-0.345	-0.285	-0.315	0.000	6	13	0.462
-0.285	-0.345	-0.094	0.188	0.047	-0.240	7	15	0.467
-0.094	0.188	-0.652	0.173	-0.240	-0.258	7	15	0.467
-0.652	0.173	-1.430	-0.223	-0.827	-0.315	8	17	0.471
-1.430	-0.223	-2.286	0.750	-0.768	-0.373	9	18	0.500
0.750	-2.286	0.636	1.558	1.097	-0.498	10	18	0.556
1.558	0.636	0.390	1.723	1.056	-0.536	11	18	0.611
1.723	0.390	0.146	1.691	0.919	-0.639	11	18	0.611
1.691	0.146	-1.067	-0.004	-0.536	-0.768	13	19	0.684
-1.067	-0.004	0.764	1.581	1.172	-0.810	13	20	0.650
0.764	1.581	0.005	1.198	0.601	-0.827	14	20	0.700
0.005	1.198	0.000	0.000	0.000	-1.146	16	20	0.800

Notes: the data of series X and Y are randomly generated using E-views program

We plot the tail dependence estimator $E\{k|k \geq 1\}-1$ in Figure 3. In this graph, the y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$. These number represent the joint loss probability or the probability of contagion. We plot these numbers against the x-axis which presents the rank order of our threshold.

Figure 3. Linkage Estimator Plot

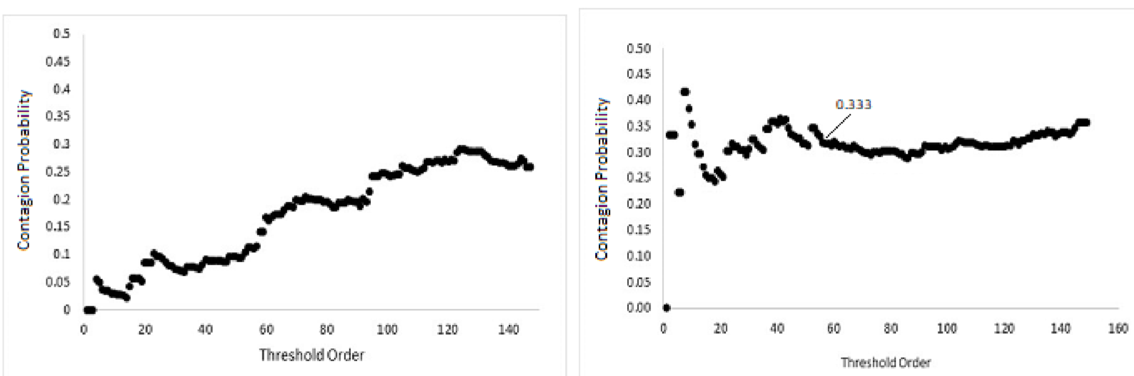


Source: Author's simulation

Our random normally distributed data generates a linkage estimator plot which shapes an upward sloping. If we increase our sample to any finite number from any types of distribution, the tail dependence estimator $E\{k|k \geq 1\}$-1 goes into 1 at the lowest threshold u. However, we focus on the early part of the plot to estimate the probability of joint crash between the two variables X and Y. In particular, we pick the data on the stable part of the graph to represent the value of dependency coefficient. This eyeballing method follows Hartmann et al. (2010) who take the expected linkage estimator by observing the stable shape of the plot. The linkage measure plot in Figure 3 above allows us to capture the strength of dependency between two financial returns.

Next, using the same data as we use to plot the Figure (2), we make a linkage measure plot as we did in the previous simulation before. Here, we can compare the different shape of simulated normal random returns distribution and the Student-t returns distribution.

Figure 4. (a) Simulated Normal Returns Distribution (b) Simulated Student T Returns Distribution



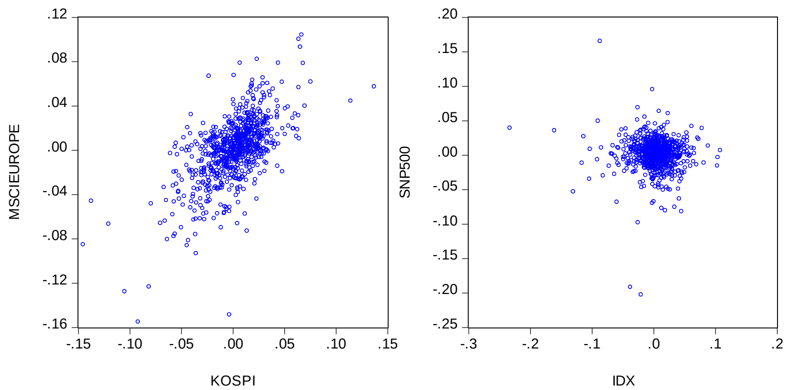
Source: Author's simulation

The linkage measure plots for the simulated normal returns distribution (a) shows an upward slope as we also seen in the previous simulation. The shape in Figure 4 (a) relatively smoother compared to the second plot. On the other hand, the simulated Student-t returns distribution in Figure 4 (b) generates a plot which immediately jumps up. This indicates the existence of asymptotic dependency between the data.

In Figure 4 (b), we see that the plot is initially unstable at the early part of observation but rapidly stable. The unstable part reflects the bias estimator area. Thus, using eyeballing method, we mark the data which located on the relatively stable plateau as the value of the linkage coefficient. The Figure 4 (b) above shows the dependency value of 0.333. This value is the expectation linkage measure $E\{k|k \geq 1\}-1$ as we mentioned in the formula (10). This value implies that there is 33.3% probability of joint crash given that one market experiences a crash.

We extend this session by using real data of weekly market returns between the US, Europe and emerging Asian countries. First, we present the scatter-plots of bivariate stock market returns in Figure 5. Figure 5 (a) shows the MSCI Europe market returns against South Korea Kospi and Figure 5 (b) shows the US S&P500 against Indonesia IDX market returns. The sample spans from January 2003 to December 2017 (780 weekly observations). In both cases, it covers well-known episodes of the US subprime crisis and the European sovereign crisis. We compute the returns as log difference between two consecutive observations of the indices.

Figure 5. Scatter Plot (a) shows the dependency at the tail where Scatter Plot (b) does not show dependency.

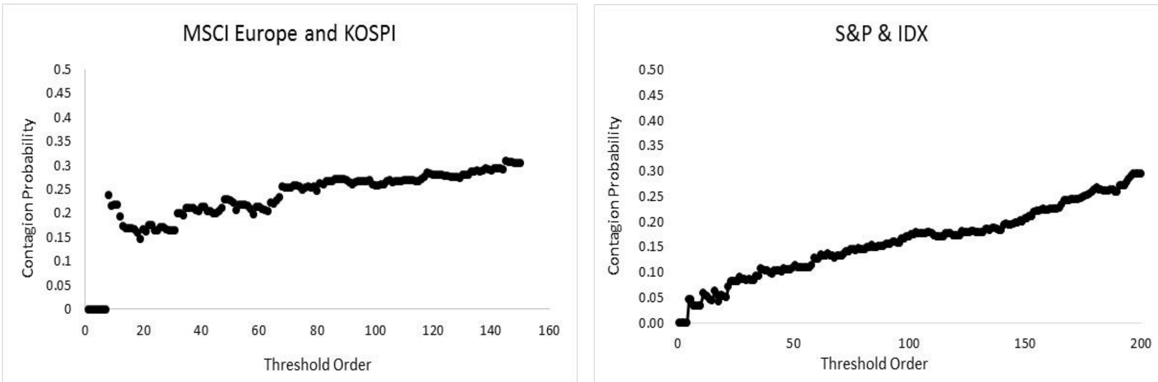


The scatter plot of the *MSCI/KOSPI* (Europe and South Korea stock market returns) in Figure 5 (a) shows a diagonal line up with outliers in the upper and lower quadrants. This graph captures the asymptotic dependency. This represents the persistent extreme on both positive and negative returns value. In this figure, the distribution of market returns which exhibit many outliers in the tail indicates the existence of contagion.

Contrary from the Figure 5 (a), in Figure 5 (b), a pair of two market returns of *S&P/IDX* (the US and Indonesia market stock returns) show a more centralised scatter plot. In this figure, most of the returns in the observations are located in the center of the distribution. This implies a much weaker dependency of their tails, suggesting asymptotic independency between variables. The weak extremal dependence between these two market returns in Figure 5 (b) illustrates the low probability of extreme values in each tail for one variable coinciding with the extreme values of another variable.

Next, we use the more formal measure of tail dependence estimator from formula (10) $E\{k|k \geq 1\}-1$. From the same data as we use in Figure 5, we provide graphic evidence of the existence of tail dependency of stock market returns in Figure 6 below.

Figure 6. Linkage Measure Plots (a) Student-t distribution (b) Normal distribution



Related to the previous scatter plot in Figure 5, we can observe the shape of the distribution of the pair of market stock return from the linkage measure plots above. The left picture of Figure 6 represents the Student-t data which is indicated by the immediate jumps in the initial part of the observation. This observation shows that the pair exhibits a linkage coefficient of 1.2381. This value implies that the probability of joint crash between these two markets is 23.8%. In other words, almost one out of four crashes is a joint crash.

In contrast to Figure 6 (a), the pair S*&P/IDX* exhibits a smoother shape which indicates the normal shape of the data distributions. This observation shows no dependence between two markets. It implies that there is almost zero probability of joint crash between these two markets given one market experiences a crash.

In Appendix B, we show some plots of the combination of the pair of bivariate variables that we observe in this thesis. We apply a similar method to the bank stock returns to indicate the existence of systemic risk. We follow the study of Hartmann et al. (2005) who examine the interdependencies of banks' stock returns in the U.S and the Euro area and in both banking systems to indicate the occurance of systemic risk. Their findings suggest that US banks exhibit high dependency within the institutions in the system which signal lower stability compared to the European banking system. This result implies the vulnerability of systemic stability in the US banking system.

4.2 Data and Descriptive Statistics

In this thesis, we use the weekly data from January 2003 to December 2017. In total, there are 780 observations for each variable. We chose a frequency of a week rather than a day since series based on daily returns are not appropriate for making inference on linkages due to differences in time zones. Furthermore, we also cover the analysis of bank stock dependency using weekly data as bank stock returns in our observation exhibited many zero return values which can potentially cause bias in our analysis.

The data of the countries originating the crisis and their associated indices are the U.S. (S&P 500), Europe (MSCI Europe Index), Germany (DAX 30), United Kingdom (FTSE 100), Italy (FTSE MIB), Spain (IBEX 35), and France (CAC 40). Meanwhile, the five Emerging Asian Countries and their associated indices that we cover in this thesis are Indonesia (IDX), Malaysia (KLCI), Thailand (SET), Philippines (PSEI), Singapore (STI), and South Korea (KOSPI). We obtain all data from the Datastream database. The market returns are calculated as follows:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{10}$$

Where P_t denotes the market stock price at time *t*.

Table 3 presents the descriptive statistics and correlation matrix of stock returns in these regions.

Table 3 Summary Statistics

Crisis Origin Countries	Market Indices	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
United States	S&P500	0.0014	0.0030	0.1653	-0.2026	0.0230	-1.5505	21.0560	10908.0800	0.0000
Europe	MSCI Europe	0.0009	0.0033	0.1042	-0.1551	0.0287	-0.7352	6.4136	448.9773	0.0000
United Kingdom	FTSE100	0.0008	0.0026	0.0867	-0.1213	0.0221	-0.7388	7.2412	655.5599	0.0000
Germany	DAX30	0.0019	0.0037	0.1061	-0.1470	0.0280	-0.4877	5.7554	277.6714	0.0000
France	FRANCECAC40	0.0007	0.0032	0.1035	-0.1408	0.0269	-0.4621	5.5405	237.5198	0.0000
Italy	FTSEMIB	-0.0001	0.0029	0.1111	-0.1470	0.0311	-0.5246	5.7054	273.6554	0.0000
Spain	IBEX35	0.0007	0.0032	0.1420	-0.2163	0.0319	-0.6104	7.1584	610.4206	0.0000
Emerging Asia Countries										
Indonesia	IDX	0.0034	0.0045	0.1081	-0.2330	0.0294	-1.2894	11.1780	2389.7010	0.0000
Malaysia	KLCI	0.0013	0.0016	0.0672	-0.0840	0.0169	-0.4238	5.9873	313.3866	0.0000
Thailand	SET	0.0020	0.0038	0.1255	-0.1785	0.0275	-0.7745	6.8224	552.8337	0.0000
Phillipines	PSEI	0.0027	0.0037	0.1105	-0.1402	0.0279	-0.4205	5.4225	213.7107	0.0000
Singapore	STI	0.0012	0.0027	0.1547	-0.1170	0.0236	-0.1118	7.9594	800.9689	0.0000
South Korea	KOSPI	0.0017	0.0043	0.1371	-0.1452	0.0267	-0.5684	6.8260	517.7501	0.0000

	S&P 500	FTSE100	FTSEMIB	FRANCECAC40	DAX30	IBEX35	IDX	KLCI	SET	STI	PSEI	KOSPI
SNP	1	-0.042	-0.048	-0.053	-0.054	0.370	-0.064	-0.056	0.343	-0.060	-0.086	0.568
FTSE100	-0.042	1	0.774	0.881	0.807	0.061	0.421	0.411	0.129	0.614	0.419	0.103
FTSEMIB	-0.048	0.774	1	0.888	0.824	0.023	0.401	0.396	0.075	0.556	0.374	0.063
FRANCECAC40	-0.053	0.881	0.888	1	0.922	0.034	0.436	0.410	0.115	0.607	0.414	0.098
DAX30	-0.054	0.807	0.824	0.922	1	0.033	0.432	0.404	0.140	0.607	0.397	0.082
IBEX35	0.370	0.061	0.023	0.034	0.033	1	-0.029	0.031	0.117	0.035	-0.005	0.196
IDX	-0.064	0.421	0.401	0.436	0.432	-0.029	1	0.598	0.059	0.592	0.582	-0.017
KLCI	-0.056	0.411	0.396	0.410	0.404	0.031	0.598	1	0.013	0.609	0.527	-0.025
SET	0.343	0.129	0.075	0.115	0.140	0.117	0.059	0.013	1	0.097	0.018	0.486
STI	-0.060	0.614	0.556	0.607	0.607	0.035	0.592	0.609	0.097	1	0.563	0.024
PSEI	-0.086	0.419	0.374	0.414	0.397	-0.005	0.582	0.527	0.018	0.563	1	-0.024
KOSPI	0.568	0.103	0.063	0.098	0.082	0.196	-0.017	-0.025	0.486	0.024	-0.024	1

First, to indicate the fat tail of the distribution of returns, we check the value of skewness and kurtosis of the market returns. The descriptive statistic result shows that all market stock returns exhibit negative skewness, meaning that extreme negative returns are a dominant feature of all markets. Furthermore, all market returns show an excessive kurtosis value above three, indicating that the distribution of those market returns is non-normal and asymmetric. The Jarque-Béra test of normality also supports this finding by rejecting the null hypothesis that the distribution follows a normal distribution at a 95% confidence level. This result is consistent with the characteristics of fat tails as seen in the data for financial returns.

Furthermore, we also observe the stock return distributions of several banks to assess the bank channel contagion and systemic risk in the Asian emerging countries. The descriptive statistics and the correlation test we use is provided in the appendix. In general, our observations show that all returns do not follow a normal distribution and they have common characteristics of sharp peaks and heavy tails as previously discussed. These characteristics can be seen based on the high kurtosis values which range between 5.0 and 45.1 and the skewness scores that are not equal to zero. These values prove that our data exhibit heavy tails. Therefore, analysing the asymptotic dependency of these data seems valid and interesting. We now turn to investigate whether there is also an asymptotic dependency between the returns.

5. Results and Discussion

We start our empirical analysis of extreme dependency between stock markets by examining the contagion risk of the recent Global Financial Crisis to the Asian emerging economies. We first present the aggregate results of market return dependency of pairs of stock indices that comprised of crisis-origin countries and the emerging countries in Asia. We then explain the dependency between bank stock returns of crisis origin countries and emerging Asian countries to indicate the existence of the bank-channel contagion. Lastly, we observe the systemic risk based on the dependency of banks within the domestic banking systems in the emerging countries in Asia. We use scatter plots and tail plots between pairs of stock returns to assist our interpretation.

5.1 Summary of Research Findings

Market Stock Dependency

Table 4. Extreme Bilateral Market Linkages across Border

Market Stock Dependence							
	US	MSCI Europe	UK	Germany	France	Italy	Spain
Indonesia	1.000	**1.206**	**1.127**	**1.156**	1.125	1.163	1.018
Malaysia	1.130	1.126	1.083	1.119	**1.143**	1.000	1.000
Thailand	1.140	**1.171**	1.103	1.071	1.077	1.067	1.088
Phillipines	1.130	**1.146**	**1.079**	1.000	**1.105**	**1.095**	1.059
Singapore	**1.218**	**1.176**	**1.286**	**1.255**	**1.316**	**1.200**	1.160
South Korea	**1.197**	**1.254**	**1.198**	**1.259**	1.244	1.163	1.046

Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for market returns pairs. These values are obtained from the calculation of formula (10) in part 4.1.3 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

The U.S. stock market is by far the largest stock market in the world and has the most considerable influence on all the other stock markets. From this stylized fact, we expect the presence of extreme dependency between the U.S. stock market and stock markets in other countries. However, the results suggest that the estimated probability of an emerging Asian stock market experiencing a crash given a crash in the U.S. market is much lower than expected.

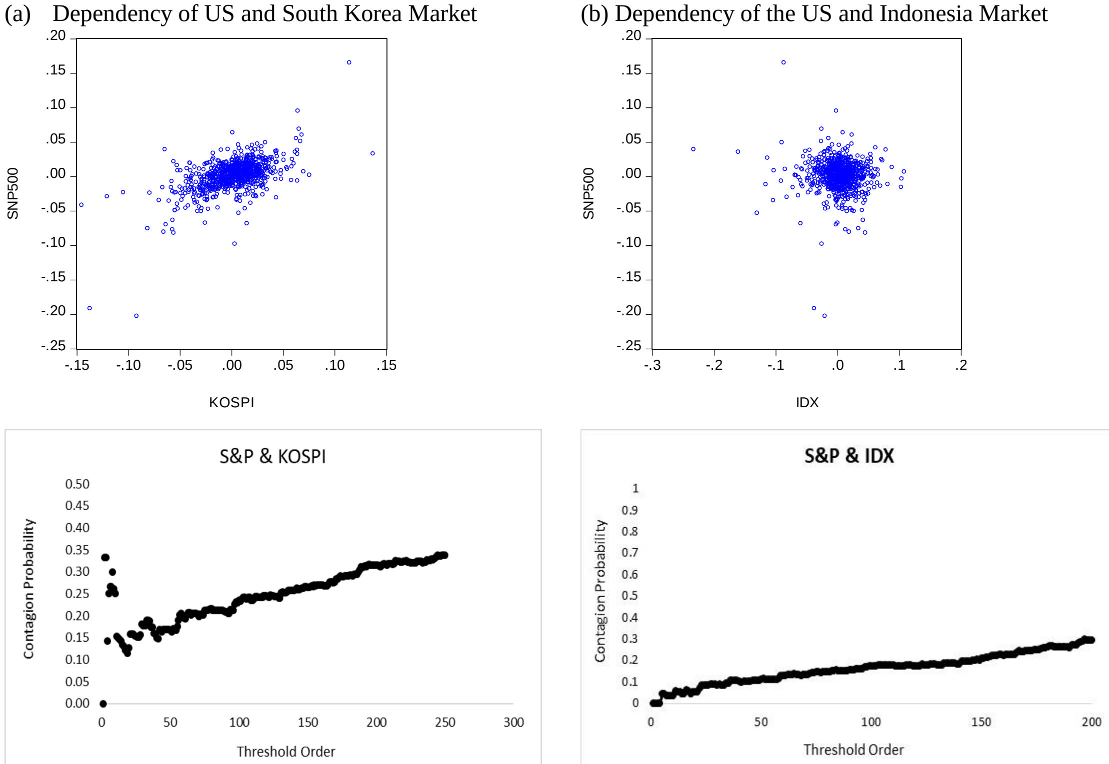
We observe that a country with a relatively large stock market has a much larger dependency as compared to those with a relatively small market. Considering the scenario when the U.S. stock market suffers an extreme loss, only stock markets in Singapore and South Korea experienced extreme losses. South Korean stock market has been found to have the strongest link with the U.S. stock market. We can see the strong dependency between the US and South Korea markets by observing the scatter plots of bivariate market returns as shown in Figure 7 (a). The diagonal line shape of scatter plots and outliers in the lower quadrant suggests the existence of extreme dependencies between the two markets.

We confirm this finding by observing the linkage estimator plots which display an immediate jumps of return distributions shappe. Using the eyeballing method as we mentioned in the section 4.1.4 Application of Bivariate Extreme Dependency, we found that the extreme dependency score for *S&P/KOSPI* (the U.S. and South Korea) is 19.7% and for *S&P/STI* (the U.S. and Singapore) is 21.8%. These findings imply that the probability of joint crash given a crash in the U.S stock market is around one out of five crashes in the South Korean and Singaporean case.

At the same time, the dependency between the U.S. stock market and the rest of the emerging countries stock markets (Indonesia, Malaysia, Thailand, and the Philippines) is relatively small. The scatter plots of the dependency between the U.S. stock market with these small size stock markets do not show any observable diagonal line, thus suggesting independency between these markets.

Figure 7. Extreme Dependency between US and emerging Asia Countries

(a) Dependency of US and South Korea Market (b) Dependency of the US and Indonesia Market



Next, we estimate the dependency between the European market and the emerging Asian countries. First, we use the MSCI (Morgan Stanley Capital Index) Europe Indices to indicate the general dependency between the European stock markets and the emerging Asian stock markets.

From six pairwise correlations, only the Malaysian stock market shows no dependency with the general European stock market returns. The highest extreme dependency is shown between the South Korean and the European stock markets with a coefficient of 25.4%. This implies that one out of four crashes in the European stock markets causes a crash in the South Korean stock market.

We extend our analysis by looking deeper into the dependencies between five European countries (UK, Germany, France, Italy, and Spain) and the six emerging Asian countries. Similar to previous results, we found a relatively high dependency between the stock market returns in Europe and the more advanced economies in Asia, as represented by the Singaporean stock market. The coefficient of the dependency between *STI/FTSE100* (Singapore and the UK) is 28.6% and *STI/CAC40* (Singapore and France) is 31.6%. Meanwhile, we found low evidence of tail dependence between Europe, Thailand and Malaysia stock market returns.

One possible explanation for the extreme dependency between the U.S. and European stock market with the Singaporean and South Korean stock markets is due to the size of these two markets, which are among the largest in Asia. Meanwhile, Malaysia shows no dependency with the European stock market due to the relatively low market transaction between these markets. Furthermore, the higher dependency coefficient between Singapore/UK market returns relative to Singapore/UK market returns represents the higher linkage between their capital markets. We assume that there is more market transaction between these markets. Another probability is that there are more France firms listed in the Singapore market, compared to UK, and vice versa. As suggested by Eichengreen (1996), the high linkage between these markets forms an important channel for crisis propagation.

Table 5. Extreme Bilateral Stock Market Linkages Intra-Asia

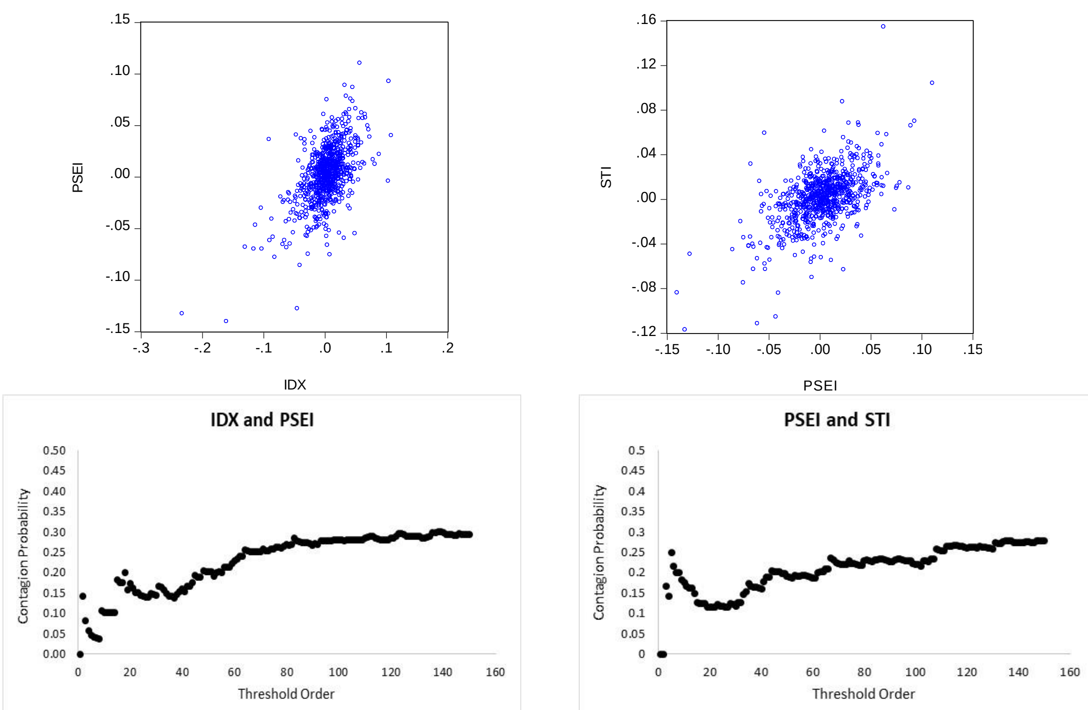
Intraregional Stock Dependence						
	Indonesia	Malaysia	Thailand	Phillipines	Singapore	South Korea
Indonesia	-					
Malaysia	**1.1087**	-				
Thailand	**1.2368**	1.1500	-			
Phillipines	**1.2000**	**1.1574**	**1.1373**	-		
Singapore	**1.2632**	**1.2800**	1.2773	**1.2500**	-	
South Korea	**1.2468**	1.1273	**1.1143**	1.2174	**1.2500**	-

Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for market returns pairs. These values are obtained from the calculation of formula (10) in part 4.13 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

Next, we observe the market stock dependence within the emerging Asian region. Table 5 contains estimations on extreme linkages across emerging Asia stock markets. From our observations, we found high dependencies between stock markets in this region. For further evidence, we provide two examples of our finding in the Figure 8 below. In this figure, we see the asymptotic dependencies between IDX/PSEI (Indonesia and Philippines stock market) and STI/PSEI (Singapore and Philippines stock market). These findings are also confirmed by the shape of the linkage estimator plots which display an immediate jump, indicating the presence of dependencies between the stock returns. This illustrates the relevance of the phenomenon of contagion as a consequence of common shocks in this region.

Figure 8. Extreme Linkages of Intra-regional Asia Stock Market

(a) Dependency of Philippines and Indonesia Market (b) Dependency of Singapore and Philippines Market



Bank Stock Dependency

We observe the presence of bank contagion from the dependency between bank stock returns across the region. We interpret dependency between banks across region as an interconnectedness that reflects the potential occurrence of the bank-contagion.

We choose the six largest banks from each crisis-origin countries and pair them with eight largest banks in the emerging Asian region. Considering the size, we assume that these banks are the most relevant object of this research given the assumption that these banks pose the largest systemic risk to the banking systems. The European banks that we chose as our samples are among the Global Systemically Important Bank (G-SIB) in Europe based on European Parliament Publication (2017). The emerging Asian banks that we chose as our samples are the largest bank in the region by total asset (Forbes, 2017).

We create all possible pairwise combinations of banks across region. The coefficient of dependency explains the probability of one bank failing, conditional on the failure of another bank. We expect that there might be a cross-border propagation of systemic risk via the dependency in stock returns of these banks.

Table 6. Extreme Bilateral Bank Stock Linkages

	JP Morgan	RBS	Deutsche Bank	BNP Paribas	Unicredit	Banco Satanders
DBS	1.0400	1.0556	1.1250	1.0500	1.0000	1.0556
OCBC	**1.0909**	1.0588	**1.0588**	**1.0417**	**1.0000**	1.1053
CIMB	**1.0909**	1.0000	**1.0323**	1.0455	1.0303	**1.0435**
Bangkok Bank	1.0000	1.0000	1.0333	1.0000	1.0303	1.0714
Siam Bank	1.0000	1.0263	1.1071	1.0476	1.0370	1.0625
Kasikorn Bank	1.0909	1.0000	1.0000	1.0417	1.0000	1.0476
Bank Mandiri	1.0526	1.0000	1.1034	**1.1250**	1.1000	1.0000
Bank BRI	1.0769	1.1429	1.2000	1.1429	1.1111	1.0556

Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for bank stock returns pairs. These values are obtained from the calculation of formula (10) in part 4.13 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

Table 6 shows that only a few banks in the crisis-origin countries have an extreme dependency to banks in the emerging Asian region. The highest coefficient of dependency between banks from advanced economies can be seen in the case of *JP Morgan/OCBC*, *JP Morgan/CIMB* and *Deutsche/DBS*, which have coefficient values of around 10%. Several pairs of banks show independency which contradicts our hypothesis on bank contagion across the region. The low dependencies between these banks might reflect low business interactions between these banks.

Table 7. Extreme Bilateral Bank Stock Linkages Intra-Asia

	DBS	OCBC	UOB	Maybank	CIMB Malaysia	Public Berhad	Bangkok Bank	Siam Bank	Kasikorn Bank	Bank Mandiri
DBS	-									
OCBC	**1.322**	-								
UOB	**1.370**	**1.3910**	-							
Maybank	**1.164**	1.143	1.222	-						
CIMB Malaysia	**1.125**	1.091	1.083	**1.111**	-					
Public Berhad Malaysia	1.000	**1.045**	1.059	**1.100**	**1.125**	-				
Bangkok Bank	**1.138**	1.042	1.074	1.000	**1.056**	**1.067**	-			
Siam Bank	1.043	1.000	1.000	**1.111**	1.071	**1.071**	**1.333**	-		
Kasikorn Bank	1.043	1.000	1.053	1.000	1.031	**1.037**	**1.250**	**1.333**	-	
Bank Mandiri	1.085	1.059	1.053	1.000	1.021	1.000	**1.250**	1.000	1.059	-

Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for bank stock returns pairs. These values are obtained from the calculation of formula (10) in part 4.13 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

We also investigate the dependency between these Asian banks as reported in Table 7. In this analysis, we use the top 10 largest assets banks from each country. From our observation, *Bangkok Bank/Bank Mandiri* exhibit the highest coefficient of dependency of 25%. However, the pairs of Singapore and Malaysian banks show asymptotic dependencies one to another. A pair of *DBS Singapore/Maybank Malaysia* has a coefficient of dependency of 16.4%. This coefficient of dependency implies that there is roughly around 16% probability of occurrence of a joint crash if one of these banks experiences a crash.

Market-Bank Stock Dependency

Table 8. Extreme Bilateral between Market Stock-Bank Stock Return

Market-Bank Stock Dependence					
Indonesia-IDX		Malaysia-KOSPI		Thailand-SET	
Bank Mandiri	**1.079**	Malayan	**1.180**	Bangkok Bank	**1.167**
BRI	**1.088**	CIMB	**1.041**	Kasikorn Bank	**1.184**
BCA	**1.148**	Public	**1.170**	Siam Bank	**1.192**
BNI	1.086	RHB	1.062	Krungthai	1.000
Niaga	1.081	Hong Leong	1.079	TMB Bank	1.000
Danamon	1.061	AMMB	1.054	Ayudhya	**1.187**
Permata	1.067	Affin	1.059	Thanachart	**1.161**
Panin	1.100	Alliance	1.128	Kiatnakin	1.000
Maybank	1.100	BIMB	1.051	CIMB Thailand	1.043

Market-Bank Stock Dependence					
Phillipines-PSEI		Singapore-STI		South Korea-KOSPI	
Phillipines Saving	1.068	DBS	1.190	Shinhan	1.155
Security Bank	**1.057**	Overseas Chinese Bank	**1.182**	KB Financial	**1.067**
BDO Unibank	1.048	UOB	**1.167**	Woori Bank	1.000
Union Bank Phillipines	**1.149**			Industrial Bank Korea	**1.100**
Phillipines National Bank	1.000			Jeju Bank	**1.100**
China Banking	1.071				
Metropolitan Bank	**1.069**				
Phillipines Bank Isle	1.100				
Rizal Com Bank	1.000				

Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for market-bank stock returns pairs. These values are obtained from the calculation of formula (10) in part 4.13 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

We investigate market-to-bank stock dependency to indicate the bank channel contagion in the emerging Asian economies. Table 8 demonstrates that not every country in this region shows a strong dependency between the country's stock market and the bank stock returns. When there is no dependency between a market and a bank stock returns, a failure in one bank does not disrupt the market, and vice versa. Therefore, we can infer that the bank-channel contagion is low in these markets.

However, we can see that several pairs of market-to-bank stocks show extreme asymptotic dependencies, particularly from the large-sized banks. In Indonesia, for example, the estimate for conditional expectation is 1.148 for the *IDX/BCA* which suggests that there is a 14.8% probability that a crash in the BCA Bank leads to a crash in IDX stock market. In Thailand, five banks show an extreme dependency with SET market return, indicating the risk of bank-channel contagion in this market. The highest joint crash probability of 19.2% can be observed for Siam Bank and the Thailand Stock Exchange (SET).

Domestic Bank Stock Dependency

We investigate the systemic risk in emerging Asian banking systems by observing dependencies among pairs of domestic banks. We consider banks who have high dependency to other banks within the system are considered to have the potential to cause a systemic risk.

Our sample consists of 45 banks: Indonesia (9), Malaysia (9), Thailand (9), Philippines (9), Singapore (3), and South Korea (5). Overall, we generate a total of 157 combinations for these 6 countries. These banks are chosen based on the consideration that the stocks of these banks are actively traded in the stock market. We exclude banks that exhibit many zero returns as they may cause bias in our result. We rank these banks according to their assets size to assist our investigation on the influence of size on the coefficient of dependency.

The general result shows that extreme dependency between banks can be observed especially within the domestic banking system in these countries. As shown in Table 9 below, we found high extreme dependencies in each banking system.

Table 9. Extreme Linkages on Emerging Asia Domestic Banking System

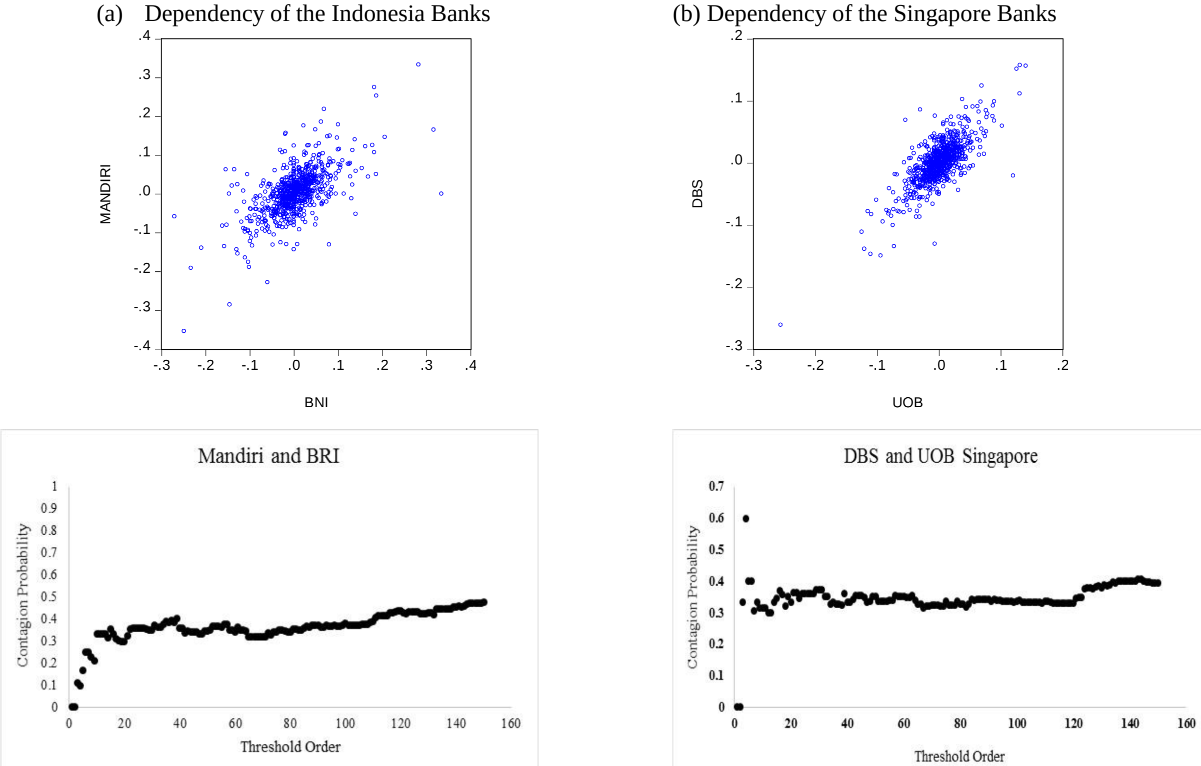
Indonesia									
	Mandiri	BRI	BCA	BNI	Niaga	Danamon	Permata	Panin	Maybank
Mandiri	-								
BRI	**1.357**	-							
BCA	**1.186**	**1.214**							
BNI	**1.227**	**1.270**	**1.167**						
Niaga	**1.227**	**1.147**	**1.080**	**1.125**					
Danamon	**1.192**	**1.333**	**1.143**	**1.188**	**1.032**				
Permata	1.077	**1.115**	1.063	1.083	1.045	1.000			
Panin	**0.148**	1.043	**1.063**	**1.111**	**1.091**	**1.111**	1.105		
Maybank	1.000	**1.063**	1.057	1.125	1.200	1.000	1.111	1.000	-
Malaysia									
	Malayan	CIMB	Public	RHB	Hong Leong	AMMB	Affin	Alliance	BIMB
Malayan	-								
CIMB	1.1250								
Public	**1.1739**	**1.2400**							
RHB	**1.0667**	**1.2727**	**1.1538**						
Hong Leong	**1.0370**	**1.0000**	**1.1429**	1.0000					
AMMB	1.2000	**1.5000**	**1.1364**	**1.5000**	1.0909				
Affin	1.0000	1.0714	1.1000	1.3077	1.0750	**1.2308**			
Alliance	**1.0625**	**1.0000**	1.1522	**1.1951**	**1.0588**	1.2456	1.1364		
BIMB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.1111	1.0000	
Thailand									
	Bangkok Bank	Kasikorn Bank	Siam Bank	Krungthai Bank	TMB Bank	Ayudhya	Thanacart Bank	Kiatnakin Bank	CIMB Thailand
Bangkok Bank	-								
Kasikorn Bank	**1.2500**	-							
Siam Bank	**1.3333**	**1.3000**	-						
Krungthai Bank	1.0714	1.0286	1.0385	-					
TMB Bank	**1.0769**	**1.1250**	**1.0714**	1.0455	-				
Ayudhya	**1.2222**	**1.1429**	**1.1000**	**1.1333**	1.1429	-			
Thanacart Bank	**1.0625**	1.0400	**1.1000**	1.0727	1.0000	1.0000	-		
Kiatnakin Bank	1.0667	1.0000	**1.1852**	1.0750	1.1429	1.0667	**1.0909**	-	
CIMB Thailand	1.0000	1.0000	1.1000	1.0588	1.0000	1.1295	1.1053	1.0667	-
Phillipines									
	PSB	Security Bank	BDO Unibank	UBP	PNB	China Bank	Metropolitan	PBI	RCB
PSB	-								
Security Bank	**1.1034**	-							
BDO Unibank	**1.1429**	**1.0278**	-						
UBP	1.0000	1.1429	1.1111	-					
PNB	1.0625	1.1333	1.0000	**1.0385**	-				
China Bank	**1.1333**	1.0556	1.1765	**1.0833**	**1.0526**	-			
Metropolitan Bank	1.0741	**1.1000**	**1.1176**	**1.6667**	1.1200	1.1411	-		
PBI	1.0313	1.1111	**1.0769**	1.2500	**1.1818**	1.0417	**1.2778**	-	
RCB	1.0303	**1.1500**	**1.1034**	1.2000	**1.2041**	1.0357	**1.1250**	1.1818	
Singapore									
	DBS	Oversea Chinese	UOB						
DBS	-								
Oversea Chinese	**1.3220**	-							
UOB	**1.3704**	**1.3910**	-						
South Korea									
	Shinhan	KB Financial	Woori	Industrial Bank	Jeju Bank				
Shinhan	-								
KB Financial	**1.3023**	-							
Woori	1.0000	1.0435	-						
Industrial Bank	1.0000	**1.3333**	1.0333	-					
Jeju Bank	1.0233	1.0847	**1.0345**	1.0345	-				

Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for bank stock returns pairs. These values are obtained from the calculation of formula (10) in part 4.13 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

In general, the results in Table 9 suggest that dependency among banks is related to their assets size. In Indonesia, for example, the state-owned banks (Mandiri, BRI, and BNI) show extreme dependencies with almost every other bank in the system. These three banks dominate the Indonesian banking sector, which comprises 35 foreign exchange banks, 30 non-foreign exchange banks, 26 regional banks, 15 joint venture banks, and 10 foreign banks. The highest coefficient of dependency in the system amounts to 35.7% which can be seen in the *Mandiri/BRI* pair. Again, this particular example demonstrates the high probability of a joint crash conditional on the failure in one of these banks.

Figure 9. Extreme Linkages in Emerging Asia Domestic Bank

(a) Dependency of the Indonesia Banks (b) Dependency of the Singapore Banks



The three largest banks by assets have extreme dependencies with other banks in the system. The number of connections increases with the size of a bank hence larger banks have a higher dependency to other banks in the system. This finding is in line with the argument that the impact of a bank to the system is related to its size.

Similar to the Indonesian banking conditions, the banking markets in Malaysia are also dominated by a few top banks. In Malaysia, the domestic banks dominate the banking system which comprises 8 domestic commercial banks, 19 foreign commercial banks, 19 Islamic banks, and 12 investment banks. Several banks show extreme dependencies with one another, such as in the case of *CIIMB/AMMB* (50%) and *AMMB/Affin Bank* (23.08%). As the Malaysian financial authorities plan to encourage more mergers between banks in their banking system in order to strengthen their banks' position as the leader financial institution in the region, the level of extreme dependency in Malaysian banking system is expected to continue to increase.

In Thailand, domestic banks dominate the banking industry with a market share of 88%. Within the Thai banking sector, our results show that the *Bangkok Bank/Siam Bank* pair has the largest value for the potential of systemic risk between bank pairs with a score of 33.33%. These two banks are the first and second largest banks in Thailand based on the size of their assets.

Meanwhile, as one of the largest financial centers in the world, Singapore's banking system comprises 5 local banks and 122 foreign banks (28 foreign full banks, 57 wholesale banks and 37 offshore banks). Three banks that we use in this study, namely DBS, UOB, and Overseas Chinese Bank, are the largest institutions in the country and cover 180% of Singapore's GDP (IMF, 2013). As it can be seen from Table 9, these three banks show extremely high dependency with the domestic market. This means that there is a high potential systemic risk within the Singapore banking system. Furthermore, these banks also show extreme dependencies with other banks in the region. Banks in Singapore have continued to grow their cross-border financing activities to strengthen their position as a financial hub in Asia. As these banks also operate in other countries in the region, they are also exposed to risks in these countries. Accordingly, a sound parent bank would provide greater stability to the banking system in the region.

5.2 Robustness Check

The crucial issues in contagion and systemic risk studies is whether the risk is changing overtime. As suggested by previous studies (see: Broadstock and Cao, 2012), the degree of dependency may evolve before and after a crisis, indicating the presence of contagion. The change in the degree of dependency in the period of economic turmoil is intuitive as there is a change in the macroeconomic environment and investor behaviour. Thus, we test the dependency level of several pairs of variables to observe the difference between the coefficient of dependency in the pre- and post-crisis period.

We use the intra-regional stock market to show the highest level of dependencies in our previous analysis. To make the comparison, we split the data into the period before the crisis, from January 2003 to June 2007, and the period which includes financial turbulence, from July 2007 to December 2017. Our results in Table 10 display significant increases in the coefficient of dependency after the crisis for regional stock indexes.

Table 10. Intra-Regional Stock Market Dependence Pre-Post Crisis Period

Intraregional Stock Dependence Before the Crisis							Intraregional Stock Dependence After the Crisis						
	Indonesia	Malaysia	Thailand	Phillipines	Singapore	South Korea		Indonesia	Malaysia	Thailand	Phillipines	Singapore	South Korea
Indonesia	-						Indonesia	-					
Malaysia	1.000	-					Malaysia	**1.2069**	-				
Thailand	1.056	1.143	-				Thailand	**1.3846**	**1.1304**	-			
Phillipines	1.000	1.000	1.000	-			Phillipines	**1.1667**	1.1000	1.0714	-		
Singapore	1.000	1.176	1.000	1.111	-		Singapore	**1.3846**	1.2000	**1.2222**	**1.3000**	-	
South Korea	1.118	1.063	1.000	1.000	1.091	-	South Korea	**1.2000**	**1.1887**	1.1000	**1.2000**	**1.2500**	-

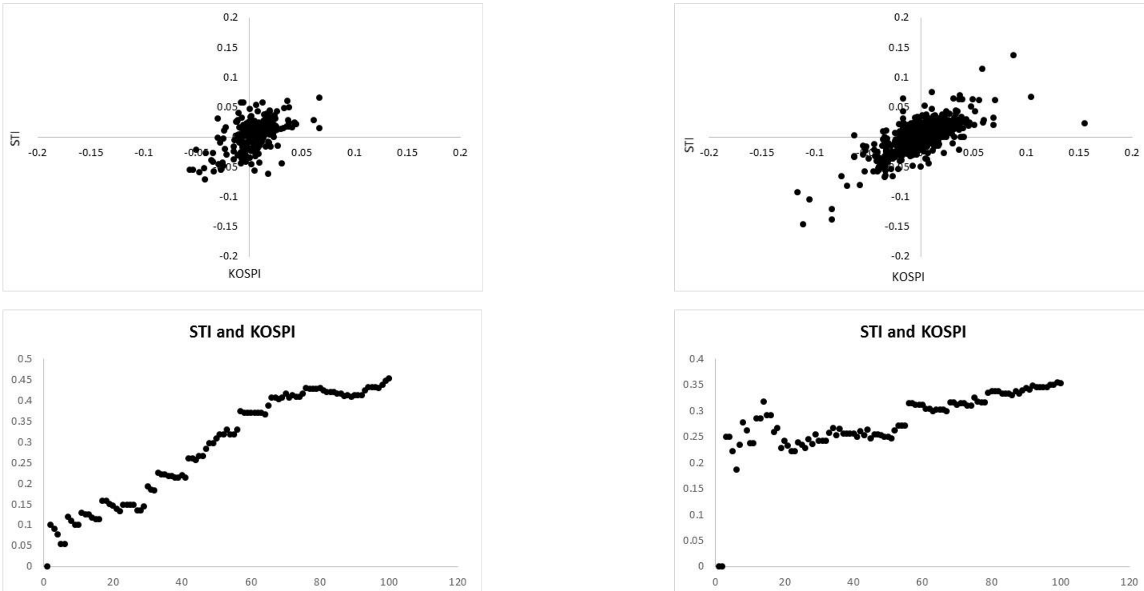
Notes: The table reports the estimated values of linkages estimator $E\{k|k \geq 1\}$ for market stock returns pairs. These values are obtained from the calculation of formula (10) in part 4.13 (Extreme Dependencies). The conditioning quantiles for the linkage estimates are chosen from the observation of shape in the linkages measure plots. The values in the table are reflecting the frequency of stock market co-crash. The bold number denotes the asymptotic dependency which we note from scatter plot observations.

The highest change in coefficient of dependency between stock market returns can be seen for returns in Singapore and South Korea. The coefficient of dependency for *STI/KOSPI* (Singapore and South Korea market stock index) increases from 9.09% before the crisis to 25% during the crisis. The change of the dependency score in these markets implies a higher probability of extreme loss in the period of crisis.

Figure 10. Scatter Plot Pre-Post Crisis Period

(a) Before the Global Financial Crisis

(b) After the Global Financial Crisis



Our exercise provides evidence of the presence of non-linear dependency in the stock market returns. The non-linear dependency is characterized by the presence of extreme dependency in a crisis period that cannot be captured in the normal period.

5.3 Economic Interpretation

Our findings imply that extreme dependency occurs between countries with a relatively large market. This can be interpreted as the *size effect of contagion*, where countries with large markets have higher dependency to other large markets. The high dependency between these markets suggests the presence of co-movement of these stock markets, further indicating that these markets would have higher probability of experiencing contagion risk when one market is experiencing a crisis. This result is intuitive as countries with larger market size typically also have more trade transactions, which in turn increases the possibility of contagion.

Our results suggest that extreme dependency appears between stock markets in the same region, indicating an intra-regional contagion. The high dependency between market returns in these countries reflects higher economic integration between these countries in the form of trade and foreign investment. When markets are more integrated, the asset prices are more in line with the international market, thus resulting in greater contagion effect in those markets. This result is in line with Hartmann, Straetmans and de Vries (2000) who found a higher probability of crashes occurring for two European stock markets than for cross-border linkages (the U.S.-Europe) in extreme events. Furthermore, the finding of intra-regional dependency can also explain why these countries is prone to speculative investor action especially during crisis period.

From our results, we also see that the dependency among banks in the same region (intra-Asia) is higher than across two different regions. This fact also brings another explanation for the existence of cross-border systemic risk in the emerging Asian region. The fundamental market argument, which suggests that financial institutions in the same region are exposed to similar macroeconomic conditions might be relevant to explain the dependency in the financial institutions in emerging Asian region. The change of interest rates in one country, for example, may create large swings of capital flows in the region (Edwards, 2000).

In the coming years, banks in the emerging Asian region are expected to expand their business within the area, rather than globally, to increase their profitability. The economic integration in this region is often seen as good for economic growth. However, economic integration can also mean an increase in dependency between (financial) institutions in this region. Banks will increasingly be more susceptible to the regional risk as their cross-border activities increase. Further analysis can use information on banks' cross-border lending to get a deeper insight on the contagion risk in the region. This result may help investors to improve their hedging strategy for their bank stocks portfolio in the region. Furthermore, it can produce a caution for financial regulators to the possibility of a regional systemic risk following a financial crisis.

Several arguments can explain extreme dependencies between large banks. The first one is related to the asset linkage, such as the inter-bank markets, portfolios, and syndicated loans. De Vries (2009) suggests that the driving factor behind the high dependency between these banks comes from their similar portfolios which translates into similar exposure to risks in the market. Another explanation for extreme dependency between these banks is due to their similar characteristics in their financing activities. When banks finance companies from the same industry, they are exposed to the similar risk that comes from the business environment. As large banks finance larger parts of the economy, and therefore have more probability to intertwine with other banks. Furthermore, as suggested by Laeven et al. (2014), large banks are riskier and have a more systemic risk as they are more engaged in complex business and market-based activities which makes them more prone to the market condition.

However, our results also suggest that big banks are not always exhibiting dependency with the rest of the institutions. For example, in Indonesia, this low dependency can be seen in *BRI/Permata* pair. The possible explanation of this low dependency is related to the difference in asset linkages and the industry sectors being financed by these banks. In this case, BRI focuses on Small Medium Enterprise (SME) financing, while Permata focuses on the corporate sector financing. The difference in their core business leads to a low dependency between these two banks. When the pair shows no dependency, the crash in one institution should not cause a systemic impact to the other institution.

Previous studies also suggest that smaller sized banks could give a relatively high systemic impact to other banks when the domestic economy is in distress. In a time of crisis, banks are prone to a sudden drop in market confidence, leading to a bank rush and also a systemic crisis in the whole system.

Merger and Acquisition (M&A) activities are expected to continue in emerging Asian banking markets. Regulators in these countries encourage acquisition of smaller banks by relatively larger banks for capital requirement reasons or as a way to save struggling small banks. Regulators provide an incentive to these larger banks by allowing them, for instance, to open new branches in designated areas. While the purpose of this program is to enhance the capital level of these institutions, at the same time this also increases the potential occurrence of systemic risk in the domestic banking system.

Notably, financial institutions in emerging Asian economies have had the highest level of interconnectedness and default risk in the Asian financial crisis, but they are relatively immune to the effects of the recent Global Financial Crisis. The development of supervision and regulatory environment in the Asian banking systems makes these banks less vulnerable and more resilient to a financial crisis than before.

The most likely reason why the dependency in countries increases in the crisis period compared to the normal period is due to the flight to quality phenomenon. Aside from the change in macroeconomic factors, the non-linearity might come due to the speculative actions of international investors as a result of a crisis in the advanced economies. In general, stock prices during the crisis period are more volatile and the emerging market are subjected to high volatility. Investors tend to make a high total capital inflow to the emerging countries when an advanced economy is experiencing an economic crisis. They tend to seek a relatively safe place to make them less exposed to high risk profiled securities. Thus, this activity results in higher transactions in the emerging market. Moreover, the crisis usually follows by a contraction in demand from the crisis origin countries. This makes the higher trade linkage during the crisis period in the emerging market. Our result is consistent with the previous studies by Moya et al. (2014) and Longin and Solnik (2001) who found the non-linear dependency during the pre-post crisis period.

6. Conclusion

In this thesis, we examine the contagion of the recent financial crises by studying the dependency between stock markets in the U.S., some countries in Europe, and some emerging countries in Asia. The empirical analysis in this thesis demonstrates the use of bivariate EVT in measuring financial risks in the international stock markets and bank stock returns. The contribution of this thesis lies in how dependency is modelled into a concrete contagion and a systemic risk analysis. We describe a measure of interconnectedness by using the bivariate EVT approach which can produce intuitive and interpretable outputs.

Several interesting conclusions come out from our analysis. One major finding is the low extreme dependency between the U.S. and emerging Asian stock markets returns. This indicates a low contagion risk between these markets. However, there is a high extreme dependency between the European and emerging Asian stock markets. Extreme dependency can especially be observed in large stock markets, such as in Singapore and South Korea. We consider this phenomenon as a size-effect contagion in which a large market has an extreme dependency with other large market.

Another important finding in this thesis is the high contagion risk in Asian countries. We find that dependency among emerging Asian stock markets is stronger than between emerging Asian stock markets and stock markets in other regions. This is reflected by the higher coefficient of dependency between markets in emerging Asian countries. A possible explanation for the strong dependency within emerging Asian stock markets is that the economic development in emerging Asian countries makes these stock markets become increasingly more integrated than before. Furthermore, bank-stock dependencies also indicate a higher result for the intra-Asian region as compared to the bank-stock dependencies across different regions.

Next, we found low dependency between a market and a bank stock returns. However, several large-asset banks show asymptotic dependency with the market stock. This implies that a failure in the large-size bank can cause disruption in the market. Therefore, regulators should pay higher attention to these banks which pose a higher risk for the financial system.

In the emerging Asian domestic banking system, we found some cases of high bivariate dependency between banks. This finding implies that the probability of occurrence of systemic risk in these countries is high. Singapore banks exhibit the highest dependencies in its domestic banking system. Thus, Singapore has the highest potential of occurrence of systemic risk in its banking system among other emerging Asian countries.

Finally, we also found the non-linearity of the strength of the dependency in the period before and after a crisis. This finding implies that interconnectedness of the emerging Asian markets increases during the period of crises.

6.1 Practical Implications

An accurate measurement of financial returns during extreme periods is useful in many applications. This study can help assist policy makers and investors alike. The two recent financial crises (the U.S. subprime mortgage crisis and the European sovereign debt crisis) revealed the urgency for the supervisory bodies to have more analytical capabilities in order to mitigate the contagion risk. We suggest two recommendations for policymakers based on our findings.

First, our recommendation is in line with the Basel Committee's recommendation to gradually update the required size-dependent capital buffers for financial institutions. As a response to the systemic risk in the system, this arrangement is beneficial to increase the resiliency of financial institutions against extreme events and thus leading to financial sector stability. Banks with a stronger capital base will have better ability to cope with major economic turmoil (Chan-Lau et al., 2012).

Second, regarding risk premium, our results emphasise the importance of imposing higher risk premiums for banks who exhibit higher dependency with other institutions in the system. As observed by Caballero and Krishnamurthy (2008) and Ibragimov et al. (2009), the systemic instability increases with the degree of dependency in the system. Furthermore, this policy will encourage banks to manage their risk by not engaging in excessive risk-taking behaviour, which can negatively impact the stability of the financial market (Schoenmaker, 2011). Moreover, we also suggest more than proportional arrangement both for capital requirements and risk premium for the larger-sized bank. This suggestion is intuitive since these banks pose a higher risk to the stability of the financial system.

Going forward, we expect regulators to require financial institutions to have a periodical stress test and put more attention to the potential occurrence of the systemic risk. By taking into account the real-time volatility of macroeconomic factors, the real-time analysis gives early detection for the policy makers and bring awareness to the shocks that are likely to happen. Accordingly, developing a proper crisis management plan is also strongly needed to anticipate the crisis, include preparing the effective recovery and resolution planning.

Moreover, our finding of the high contagion risk in the intra-regional Asia brings the importance of cross-border crisis management. The policy makers in the region should coordinate to develop the region's capacity to monitor financial risks effectively and preserve regional financial stability.

The empirical findings in our thesis also provide substantial information for investors and managers of financial institutions. International investors may consider expanding their portfolios to stock markets with low dependency to avoid the downside risk caused by the strong co-movement between markets in the event of an economic downturn. For example, international investors who engage in Indonesian and South Korean stock markets are more likely to experience higher losses once a crisis occurs in one of the countries since the coefficient of dependency between these markets is up to 50%. Therefore, hedging equity investments with another market is beneficial to reduce risk. This action explains the phenomena of flight to safety, which refers to the international diversification during a bear period (Solnik, 1974).

6.2 Limitation

The limitation of this paper lies in the methodology part. As we mentioned in the theoretical framework, there are various methods to calculate the contagion risk. In this thesis, we consider one of these methods, which is the dependency based on the tail of the distribution in the scope of the bivariate EVT framework. One major advantage of this method is its simplicity. However, this approach has several limitations. The first limitation of this approach relates to a large number of combinations of dependency that we need to investigate. The multivariate EVT can be employed for further study.

Moreover, the EVT method has limitations on its ability to detect the sources of contagion as suggested in the literature. Since the mechanism of transmission of a crisis can be complex, further study should extend our study by focusing on the use of other approaches — that incorporate several factors such investor behaviour, and macroeconomic factors— to study a crisis, contagion risk, and systemic risk.

The study of systemic risk, for example, can be extended by studying the contribution of individual risk to the system. It is also interesting to extend this study and investigate the expected aggregate monetary impact of a crisis. Future study can also look deeper into sectors and industries in each different market. As suggested in previous studies, the correlation coefficients within industries also bring contagion risk in the period of a bear market.

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8. Appendices

8.1 Appendix A: Summary Statistics and Correlation Matrix

Here we present a summary statistics table of the banks that we use in our analysis.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob
Bank Channel Contagion									
JP Morgan	0.001881	0.003438	0.284368	-0.233371	0.042498	-0.044632	9.533549	1387.595	0
Royal Bank Scotland	-0.003499	0.00031	0.532978	-1.204772	0.083499	-4.376316	66.01945	131561.9	0
Deutsche Bank	-0.001035	-0.001002	0.28136	-0.291649	0.055493	-0.281867	7.305761	612.8647	0
BNP Paribas	0.000681	0.003165	0.230258	-0.298545	0.052076	-0.440827	8.076359	862.769	0
Unicredit	-0.002261	0	0.282005	-0.332354	0.062026	-0.187668	7.156493	566.0628	0
Banco Santander	0.000428	0.001531	0.208245	-0.240639	0.045906	-0.135094	5.883207	272.5412	0
DBS	0.001259	0.001355	0.157467	-0.261457	0.035718	-0.5149	9.241216	1300.431	0
OCBC	0.001416	0.001046	0.197438	-0.268065	0.029596	-0.706216	15.65989	5273.703	0
CIMB Malaysia	0.001691	0	0.160998	-0.167107	0.034889	0.089571	5.851419	265.2871	0
Bangkok Bank	0.000964	0	0.091249	-0.068993	0.018498	0.540526	5.595571	256.9341	0
Siam Bank	0.00077	0	0.096538	-0.068319	0.01969	0.415349	5.045248	158.3757	0
Kasikorn Bank	0.001251	0	0.09963	-0.067659	0.020939	0.58078	5.451533	239.1752	0
Bank Mandiri	0.003698	0	0.33326	-0.354429	0.058217	-0.025483	8.38396	942.1628	0
Bank BRI	0.004515	0	0.27274	-0.266268	0.057961	0.234987	5.990502	297.8293	0
Indonesian Bank									
Mandiri	0.003884	0.004494	0.33326	-0.354429	0.059634	-0.033701	8.066969	786.4108	0
BRI	0.004848	0.005115	0.27274	-0.266268	0.059715	0.211674	5.638665	218.717	0
BCA	0.004309	0.003407	0.250051	-0.211758	0.043634	-0.050594	6.772812	436.2333	0
BNI	0.002449	0	0.334366	-0.270646	0.057866	0.352856	8.203939	844.6074	0
Maybank	0.001409	0	0.418028	-0.336478	0.056187	1.286172	16.05874	5425.148	0
Niaga	0.001966	0	0.385993	-0.287682	0.063226	0.288426	7.719287	692.2607	0
Panin	0.002008	0	0.292987	-0.269345	0.056695	0.145882	5.78183	239.6009	0
Permata	-5.99E-05	0	0.356669	-0.416163	0.059581	0.356614	12.95725	3051.948	0
Danamon	0.001928	0	0.359141	-0.401343	0.064789	0.046632	9.208897	1180.872	0
Malaysian Bank									
Malayan	0.000659	0	0.147165	-0.165664	0.027123	-0.317703	10.00579	1608.257	0
CIMB	0.001683	0	0.160998	-0.167107	0.03489	0.090239	5.85076	265.1806	0
Public Berhad	0.002271	0.001013	0.103784	-0.112725	0.021571	-0.387836	8.901163	1151.325	0
RHB	0.001985	0	0.208864	-0.165932	0.037214	0.411755	7.13219	576.9778	0
Hong Leong	0.001759	0	0.09441	-0.18521	0.02428	-0.467148	9.554778	1424.736	0
AMMB	0.000976	0.001556	0.184004	-0.192206	0.036623	-0.274385	7.600333	697.587	0
Affin	0.001073	0	0.240393	-0.28615	0.039096	0.407717	11.80278	2540	0
Alliance	0.00192	0	0.152108	-0.22563	0.037654	-0.196082	6.836484	483.3532	0
BIMB	0.001609	0	0.39667	-0.2004	0.041725	1.450967	17.24137	6865.231	0
Thailand Bank									
Ayudhya	0.002315	0	0.471109	-0.390275	0.054527	0.133819	15.79085	5319.521	0
Bangkok Bank	0.001822	0	0.157467	-0.30084	0.037755	-0.431101	8.943536	1172.243	0
CIMB Thailand	-0.001047	0	0.731531	-0.556811	0.062739	2.7434	45.07636	58517.05	0
Kasikorn Bank	0.002784	0	0.242641	-0.239017	0.042914	0.03825	6.091567	310.8183	0
Kiatnakin	0.001098	0	0.191667	-0.219214	0.04421	0.161318	4.589345	85.47856	0
Krungthai	0.003919	0	0.231802	-0.186586	0.056172	0.438749	4.808043	131.2682	0
Siam Bank	0.002149	0	0.174803	-0.271035	0.043414	-0.289803	5.820612	269.4833	0
Thanachart	0.001837	0	0.176704	-0.371332	0.043674	-0.790983	12.29717	2890.552	0
TMMB Bank	0.000109	0	0.329422	-0.527633	0.056168	-0.456367	18.06442	7402.521	0
Phillipines Bank									
BDO Unibank	0.00291	0	0.163629	-0.336472	0.042063	-0.707505	10.20653	1755.178	0
China Bank	0.001889	0	0.177397	-0.105361	0.02807	0.855218	9.200614	1346.353	0
Medco	0.003362	0	0.798508	-0.483427	0.111764	0.776384	10.81423	2065.527	0
Metropolitan Bank	0.001875	0	0.312665	-0.255495	0.048578	-0.016437	7.140524	557.9274	0
Phillipines Saving Bank	0.001462	0	0.203613	-0.159065	0.031782	0.776123	12.86378	3244.525	0
Phillipines Bank of Isle	0.002234	0	0.184578	-0.159842	0.037516	0.121903	5.385698	187.147	0
Phillipines National Bank	0.001165	0	0.278194	-0.208392	0.053306	0.743912	7.590977	757.9181	0
Rizal Com Bank	0.002384	0	0.283583	-0.28164	0.05089	0.67856	8.647166	1097.704	0
Security Bank	0.004694	0	0.398318	-0.19052	0.047672	0.908175	11.02569	2203.422	0
Union Bank Phillipines	0.002778	0	0.180242	-0.194207	0.036124	-0.05753	8.550499	1002.976	0
Singapore Bank									
DBS	0.001259	0.001355	0.157467	-0.261457	0.035718	-0.5149	9.241216	1300.431	0
Oversea Chinese Bank	0.001416	0.001046	0.197438	-0.268065	0.029596	-0.706216	15.65989	5273.703	0
UOB	0.001082	0	0.1407	-0.25572	0.03247	-0.552828	10.08149	1669.525	0
South Korea Bank									
KB Financial	0.000409	0	0.188966	-0.251537	0.047758	-0.244328	5.473243	206.5607	0
Shinhan	0.001696	0.001931	0.171032	-0.167507	0.045787	-0.071379	4.228842	49.73908	0
Woori	0.000352	-0.004122	0.549965	-0.502097	0.086056	0.366077	12.0939	2705.142	0
Industrial Bank Korea	0.001264	0	0.189542	-0.316693	0.051113	-0.678669	7.623665	752.7359	0
Jeju Bank	0.000971	0	0.327552	-0.201116	0.040674	0.888167	13.76875	3871.442	0

Correlation Matrix

In this appendix we present the table of correlation matrix of the banks that we use in our analysis. We can compare this table with the table of EVT analysis that we present in the Results and Discussion in Chapter 5.

	JP Morgan	Royal Bank Scotland	Deutsche Bank	BNP Paribas	Unicredit	Banco Santander	DBS	OCBC	CIMB Malaysia	Bangkok Bank	Siam Bank	Kasikorn Bank	Bank Mandiri	Bank BRI
JP Morgan	1	0.553937799	0.626730199	0.634274894	0.486019343	0.556940512	0.301612404	0.259321203	0.225511597	-0.014626492	-0.015803323	-0.064848574	0.207422312	0.109706248
Royal Bank Scotland	0.553937799	1	0.627211017	0.626055962	0.515815895	0.520864198	0.134781288	0.123203305	0.165347317	-0.00578632	0.01184542	-0.043280198	0.128125664	0.158319048
Deutsche Bank	0.626730199	0.627211017	1	0.7551362	0.700989779	0.739309501	0.228240097	0.205588545	0.198582193	-0.039499994	-0.025893078	-0.097005658	0.110161151	0.240303775
BNP Paribas	0.634274894	0.626055962	0.7551362	1	0.723606691	0.765003848	0.227680802	0.231890918	0.180595639	-0.028089148	0.004944236	-0.035540464	0.143561641	0.15923513
Unicredit	0.486019343	0.515815895	0.700989779	0.723606691	1	0.723938992	0.157148506	0.1851326	0.148675001	-0.02870621	-0.01050037	-0.072402683	0.073316766	0.19456433
Banco Santander	0.556940512	0.520864198	0.739309501	0.765003848	0.723938992	1	0.24394404	0.249566918	0.158656818	-0.009871197	0.016667696	-0.020504724	0.144183363	0.214388685
DBS	0.301612404	0.134781288	0.228240097	0.227680802	0.157148506	0.24394404	1	0.753488153	0.299455676	-0.012127949	-0.006206418	0.02594664	0.446715072	-0.01941216
OCBC	0.259321203	0.123203305	0.205588545	0.231890918	0.1851326	0.249566918	0.753488153	1	0.313796354	-0.016884617	-0.024975896	0.003672033	0.437226588	-0.017164161
CIMB Malaysia	0.225511597	0.165347317	0.198582193	0.180595639	0.148675001	0.158656818	0.299455676	0.313796354	1	0.037364757	0.005242151	-0.000271509	0.2639158	0.058677863
Bangkok Bank	-0.014626492	-0.00578632	-0.039499994	-0.028089148	-0.02870621	-0.009871197	-0.012127949	-0.016884617	0.037364757	1	0.701441719	0.710420377	-0.012391137	-0.006234973
Siam Bank	-0.015803323	0.01184542	-0.025893078	0.004944236	-0.01050037	0.016667696	-0.006206418	-0.024975896	0.005242151	0.701441719	1	0.750892276	0.003648615	0.01376034
Kasikorn Bank	-0.064848574	-0.043280198	-0.097005658	-0.035540464	-0.072402683	-0.020504724	0.02594664	0.003672033	-0.000271509	0.710420377	0.750892276	1	0.029094936	-0.040270266
Bank Mandiri	0.207422312	0.128125664	0.110161151	0.143561641	0.073316766	0.144183363	0.446715072	0.437226588	0.2639158	-0.012391137	0.003648615	0.029094936	1	-0.074285939
Bank BRI	0.109706248	0.158319048	0.240303775	0.15923513	0.19456433	0.214388685	-0.01941216	-0.017164161	0.058677863	-0.006234973	0.01376034	-0.040270266	-0.074285939	1

Indonesian Bank

	IDX	Mandiri	BRI	BNI	BCA	Niaga	Panin	Permata	Maybank	Danamon
IDX	1	0.3731233	0.3577228	0.3783228	0.3365779	0.3546386	0.2930896	0.27988413	0.1812922	0.34993535
Mandiri	0.3731233	1	0.7061773	0.6226587	0.6306472	0.5120935	0.4846402	0.30438118	0.2474561	0.57725924
BRI	0.3577228	0.7061773	1	0.6124647	0.6580919	0.4348577	0.4296044	0.22565858	0.2527903	0.5974973
BNI	0.3783228	0.6226587	0.6124647	1	0.5453615	0.3974948	0.4175709	0.26461948	0.2010238	0.51601618
BCA	0.3365779	0.6306472	0.6580919	0.5453615	1	0.4237337	0.3864772	0.23896938	0.2479352	0.52089185
Niaga	0.3546386	0.5120935	0.4348577	0.3974948	0.4237337	1	0.4035163	0.2773985	0.3670088	0.39579643
Panin	0.2930896	0.4846402	0.4296044	0.4175709	0.3864772	0.4035163	1	0.25332259	0.234899	0.36491065
Permata	0.2798841	0.3043812	0.2256586	0.2646195	0.2389694	0.2773985	0.2533226	1	0.2113058	0.22858403
Maybank	0.1812922	0.2474561	0.2527903	0.2010238	0.2479352	0.3670088	0.234899	0.21130579	1	0.22632264
Danamon	0.3499353	0.5772592	0.5974973	0.5160162	0.5208919	0.3957964	0.3649107	0.22858403	0.2263226	1

Malaysian Bank

	KLCI	Malayan	CIMB	Public	RHB	Hong Leong	AMMB	Affin	Alliance	BIMB
KLCI	1	0.290653	0.319761	0.302277	0.311329	0.2017285	-0.03426	-0.02165	0.24244663	0.012012253
Malayan	0.290653	1	0.498276	0.488649	0.414241	0.350764108	0.039438	0.013978	0.438535053	-0.01459864
CIMB	0.319761	0.498276	1	0.451548	0.456964	0.431909124	0.041551	0.052012	0.437208406	-0.003793222
Public	0.302277	0.488649	0.451548	1	0.352948	0.435585831	0.087489	0.095947	0.432833226	-0.040678019
RHB	0.311329	0.414241	0.456964	0.352948	1	0.332351137	-0.02654	-0.01165	0.43775713	-0.04103535
Hong Leong	0.201729	0.350764	0.431909	0.435586	0.332351	1	0.009824	-0.00225	0.415409368	-0.080386944
AMMB	-0.03426	0.039438	0.041551	0.087489	-0.02654	0.00982384	1	0.494678	0.036314562	0.327587727
Affin	-0.02165	0.013978	0.052012	0.095947	-0.01165	-0.00225028	0.494678	1	-0.003132972	0.38596675
Alliance	0.242447	0.438535	0.437208	0.432833	0.437757	0.415409368	0.036315	-0.00313	1	-0.04624379
BIMB	0.012012	-0.0146	-0.00379	-0.04068	-0.04104	-0.08038694	0.327588	0.385967	-0.04624379	1

Thailand Bank

	SET	Bangkok Bank	Kasikorn Bank	Siam Bank	Krungthai Bank	TMB Bank	Ayudhya	Thanacart Bank	Kiatnakin Bank	CIMB Thailand
SET	1	0.650367392	0.622513196	0.612202621	0.411547718	0.533406754	0.509023037	0.524736035	0.50670728	0.322483757
Bangkok Bank	0.650367392	1	0.779876872	0.76938219	0.361811646	0.52889248	0.581707449	0.524318505	0.483844548	0.249773309
Kasikorn Bank	0.622513196	0.779876872	1	0.830261062	0.301232876	0.475784792	0.613676064	0.507549394	0.505022033	0.280440084
Siam Bank	0.612202621	0.76938219	0.830261062	1	0.324328996	0.503708536	0.617186595	0.516181827	0.481183937	0.315418416
Krungthai Bank	0.411547718	0.361811646	0.301232876	0.324328996	1	0.330312412	0.284736511	0.322064919	0.368179759	0.164796583
TMB Bank	0.533406754	0.52889248	0.475784792	0.503708536	0.330312412	1	0.462330129	0.496146761	0.379841945	0.28072303
Ayudhya	0.509023037	0.581707449	0.613676064	0.617186595	0.284736511	0.462330129	1	0.460516292	0.393012998	0.265120955
Thanacart Bank	0.524736035	0.524318505	0.507549394	0.516181827	0.322064919	0.496146761	0.460516292	1	0.524774075	0.294009715
Kiatnakin Bank	0.50670728	0.483844548	0.505022033	0.481183937	0.368179759	0.379841945	0.393012998	0.524774075	1	0.247868982
CIMB Thailand	0.322483757	0.249773309	0.280440084	0.315418416	0.164796583	0.28072303	0.265120955	0.294009715	0.247868982	1

Phillipines Bank

	PSEI	Phillipine Saving	Security Bank	BDO Unibank	Union Bank	Phillipines National	China Bank	Metropolitan Bank	Phillipines of Isle	Rizal Com Bank
PSEI	1	0.089076417	0.30648924	0.388343776	0.333408759	0.416469613	0.243726416	0.39887995	0.37549802	0.346085641
Phillipine Saving Bank	0.089076417	1	0.113100651	0.119928403	0.071748746	0.139213991	0.068753522	0.134464851	0.094258644	0.076518714
Security Bank	0.30648924	0.113100651	1	0.401195523	0.406848996	0.411879377	0.276223459	0.422685709	0.358309767	0.360215214
BDO Unibank	0.388343776	0.119928403	0.401195523	1	0.428251366	0.402522762	0.397887981	0.626503895	0.538788885	0.338933663
Union Bank Phillipines	0.333408759	0.071748746	0.406848996	0.428251366	1	0.384740236	0.344490879	0.43389114	0.386474305	0.374229497
Phillipines National Bank	0.416469613	0.139213991	0.411879377	0.402522762	0.384740236	1	0.279093196	0.501639345	0.487091507	0.489803318
China Bank	0.243726416	0.068753522	0.276223459	0.397887981	0.344490879	0.279093196	1	0.353964796	0.282803076	0.25200421
Metropolitan Bank	0.39887995	0.134464851	0.422685709	0.626503895	0.43389114	0.501639345	0.353964796	1	0.621249318	0.435637273
Phillipines Bank of Isle	0.37549802	0.094258644	0.358309767	0.538788885	0.386474305	0.487091507	0.282803076	0.621249318	1	0.384783171
Rizal Com Bank	0.346085641	0.076518714	0.360215214	0.338933663	0.374229497	0.489803318	0.25200421	0.435637273	0.384783171	1

Singapore Bank

	STI	DBS	Oversea Chinese	UOB
STI	1	0.478489	0.474056161	0.471316
DBS	0.478489	1	0.753488153	0.761239
Oversea Chinese	0.474056	0.753488	1	0.776578
UOB	0.471316	0.761239	0.776577661	1

South Korea Bank

	KOSPI	Shinhan	KB Financ	Woori	Industrial Bank Korea	Jeju Bank
KOSPI	1	0.485843	0.519592	0.332934	0.046576247	0.275037
Shinhan	0.485843	1	0.736144	0.238785	0.062873802	0.154027
KB Financial	0.519592	0.736144	1	0.224049	0.026803777	0.203289
Woori	0.332934	0.238785	0.224049	1	0.031014244	0.206868
Industrial Bank Korea	0.046576	0.062874	0.026804	0.031014	1	0.078868
Jeju Bank	0.275037	0.154027	0.203289	0.206868	0.078867752	1

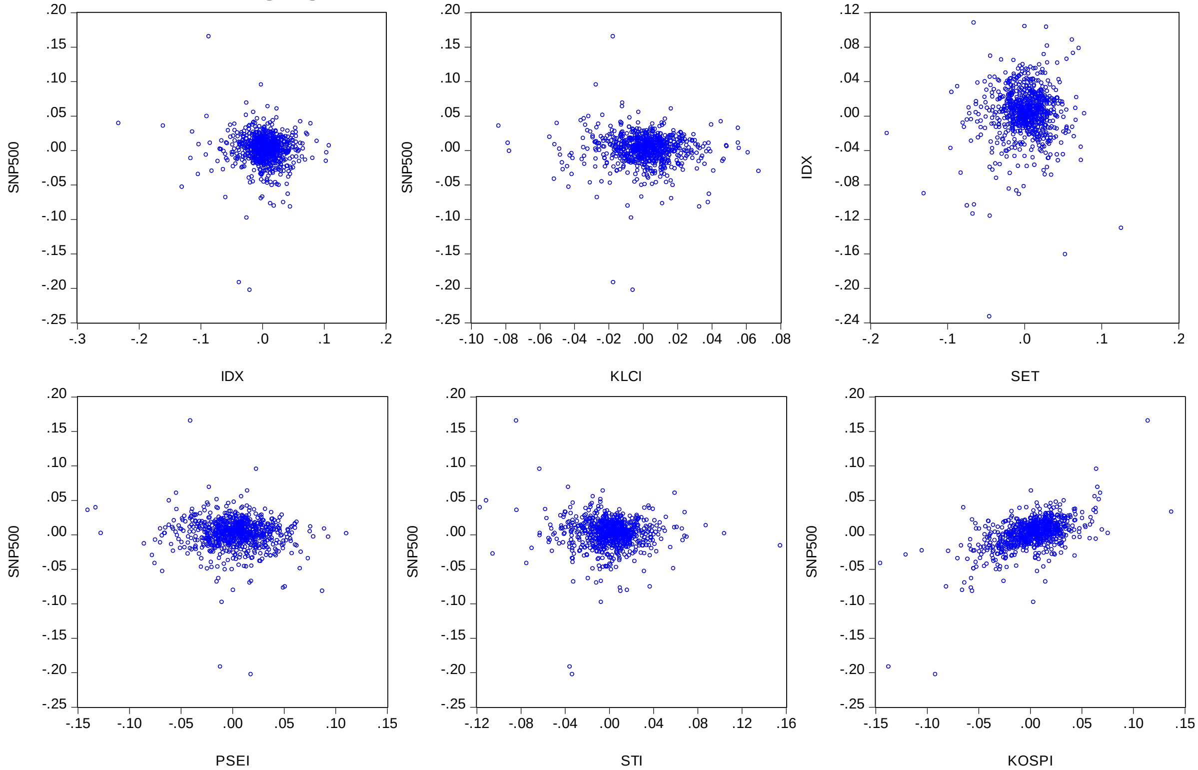
8.2 Appendix B: Scatter Plot

In this appendix, we provide scatter plots and linkages estimator plots of market and banks stock returns that we use in our analysis.

Market Return Scatter Plot

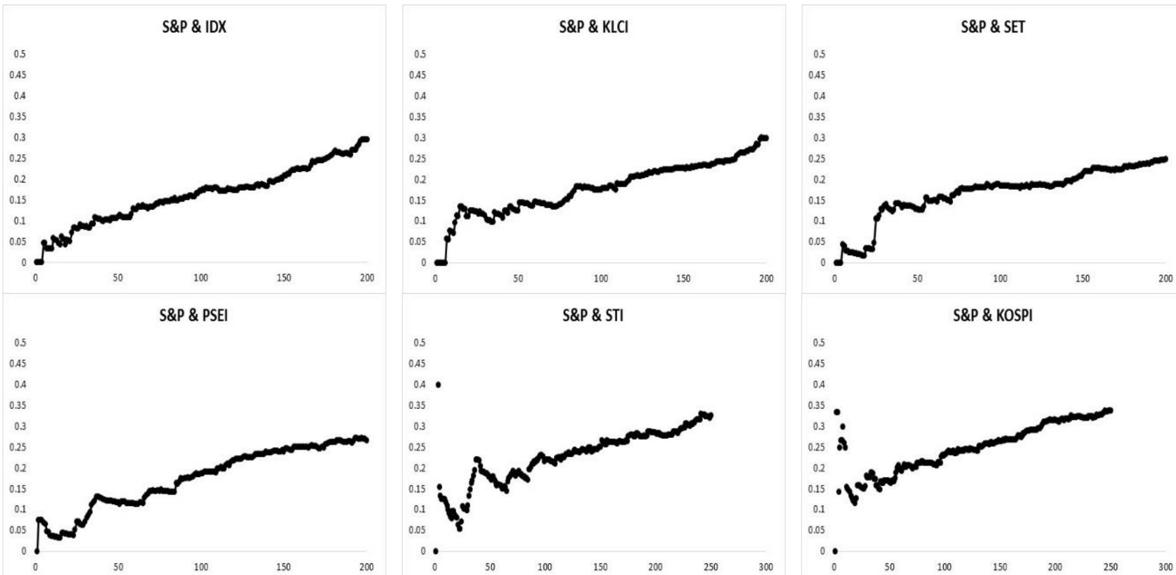
In this part, we provide the scatter plots of US and Europe market returns that we use in our analysis. We conclude the asymptotic dependency between pairs of market stocks in Table 4 in Chapter 5 part Results and Discussion.

US S&P and Emerging Asia Market Returns Scatter Plot

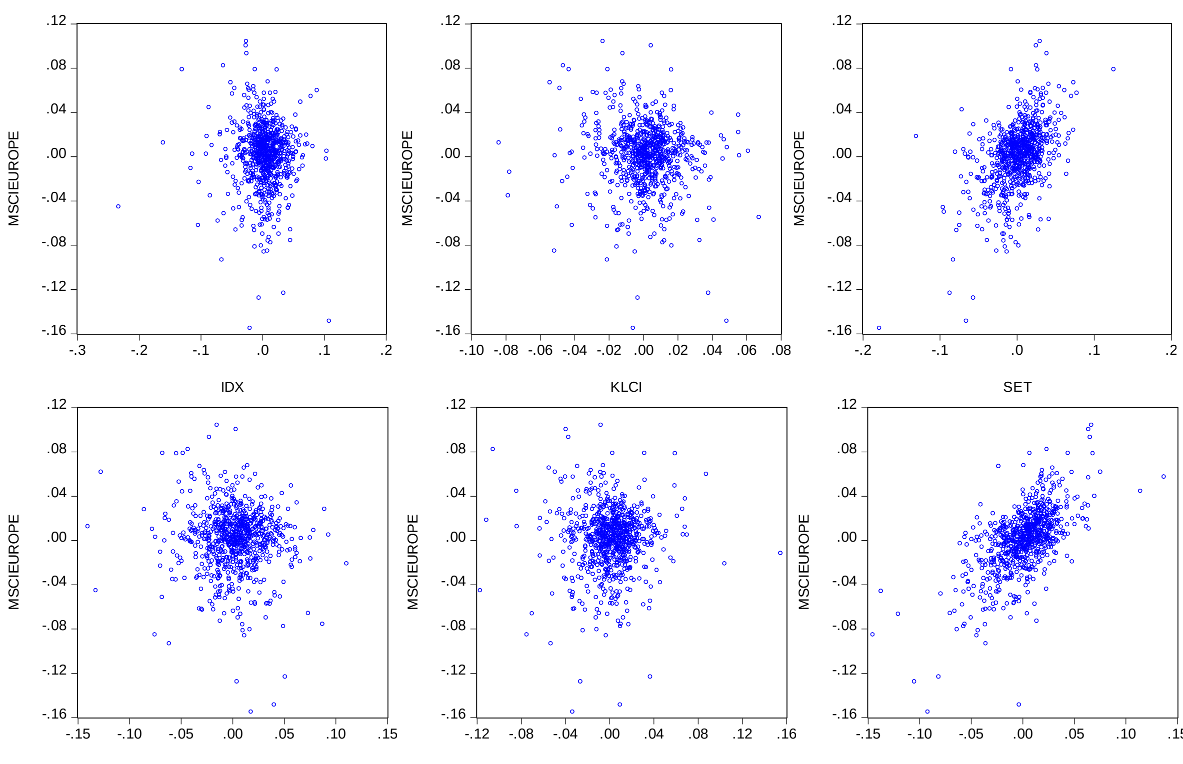


Linkage Estimator Plot: US S&P 500 and Emerging Asia Market Returns

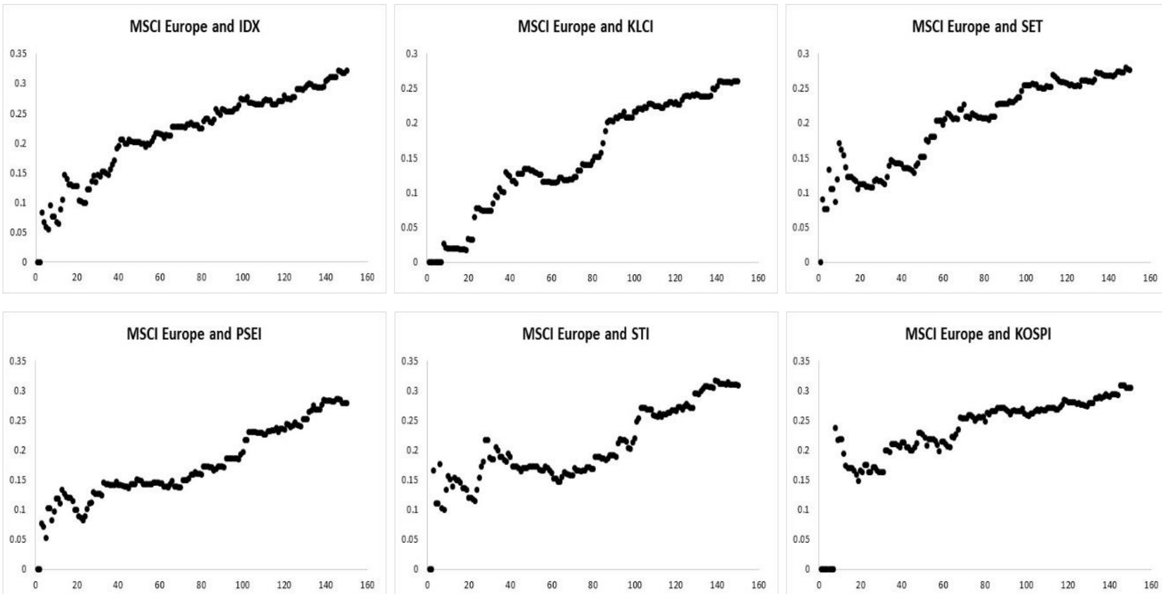
In this part, we provide the linkages estimator plots of US and Europe market returns that we use in our analysis. We conclude the probability of extreme event $E\{k|k \geq 1\}$ in Table 4 in Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.



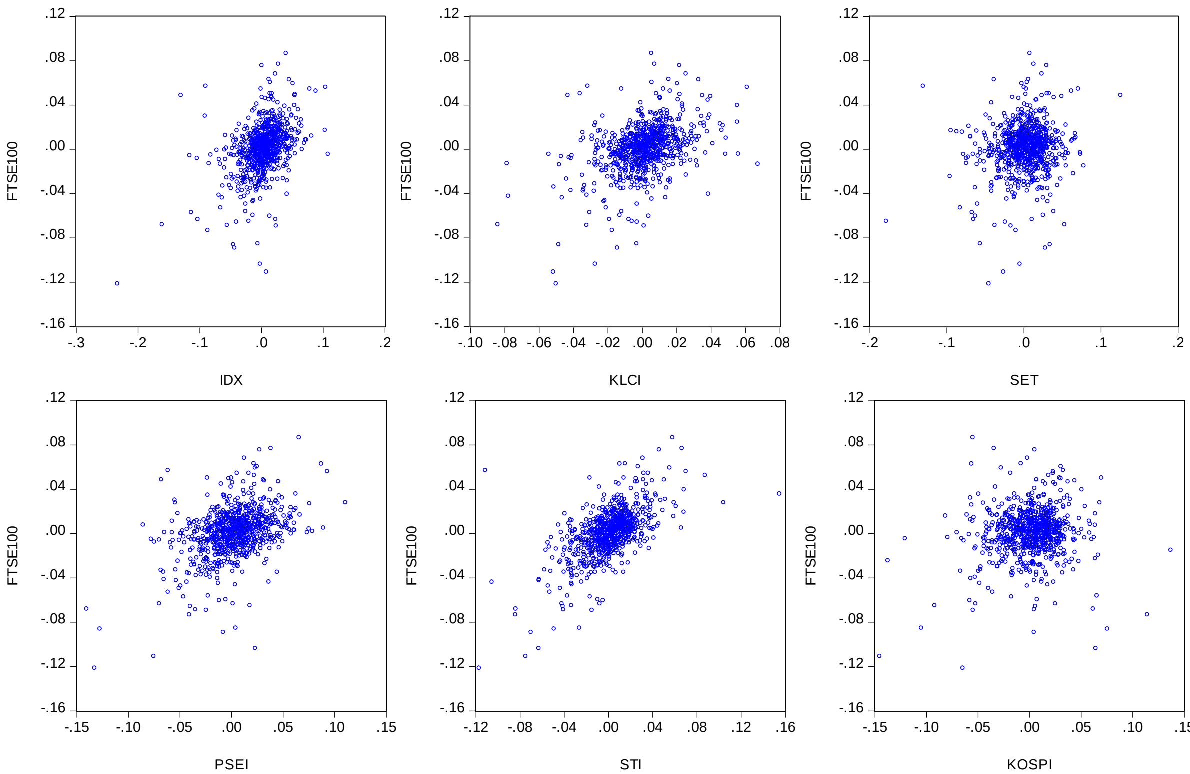
Market Indices Return Scatter Plot: MSCI Europe & Emerging Asia



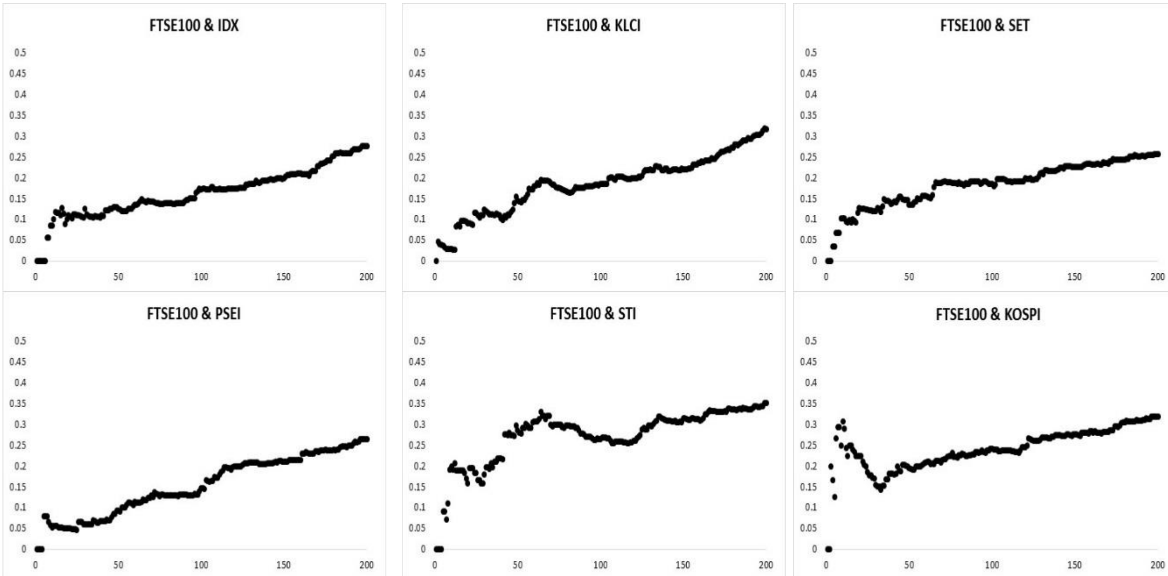
Linkage Estimator Plot: MSCI Europe and Emerging Asia Market Returns



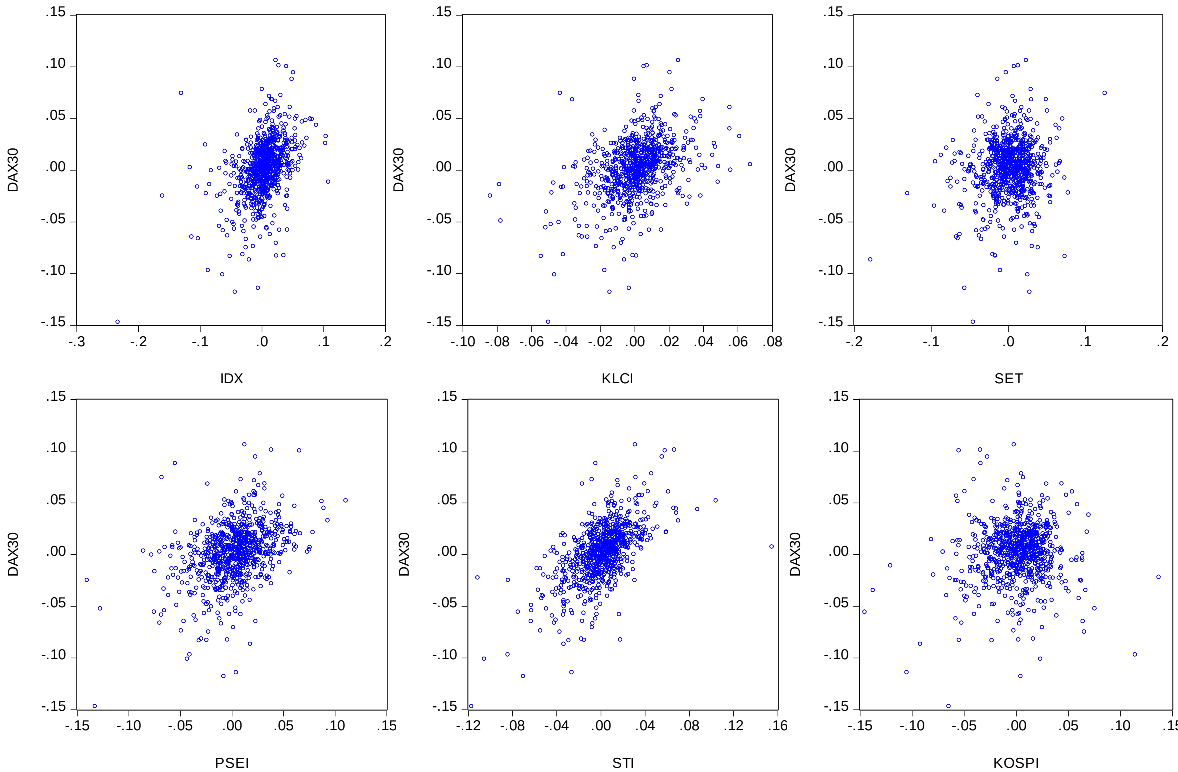
Market Indices Return Scatter Plot: UK FTSE100 & Emerging Asia



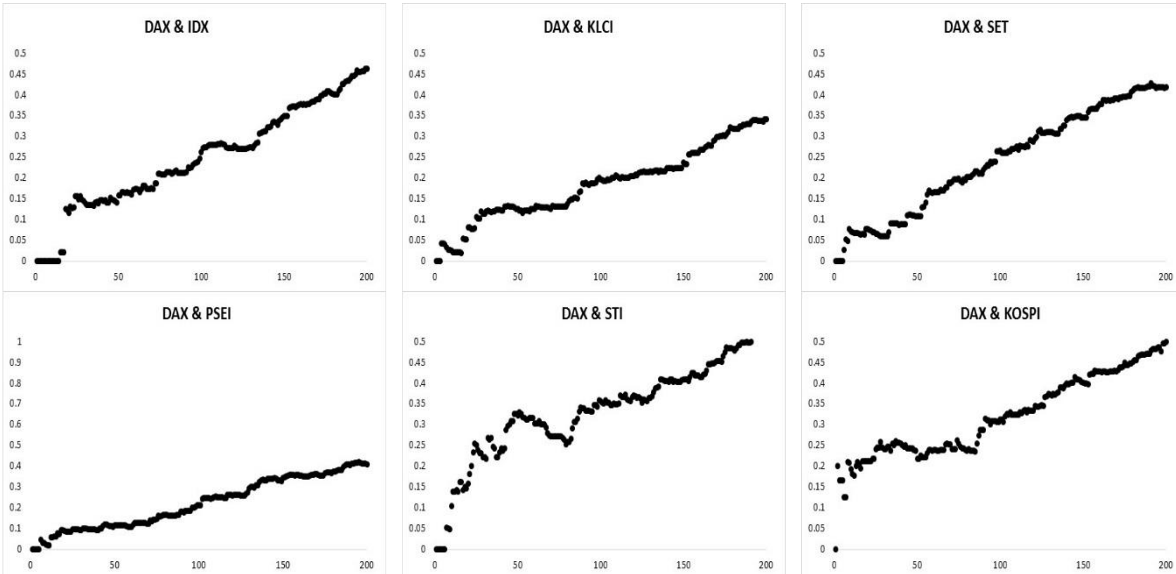
Linkage Estimator Plot: UK FTSE 100 and Emerging Asia Market Returns



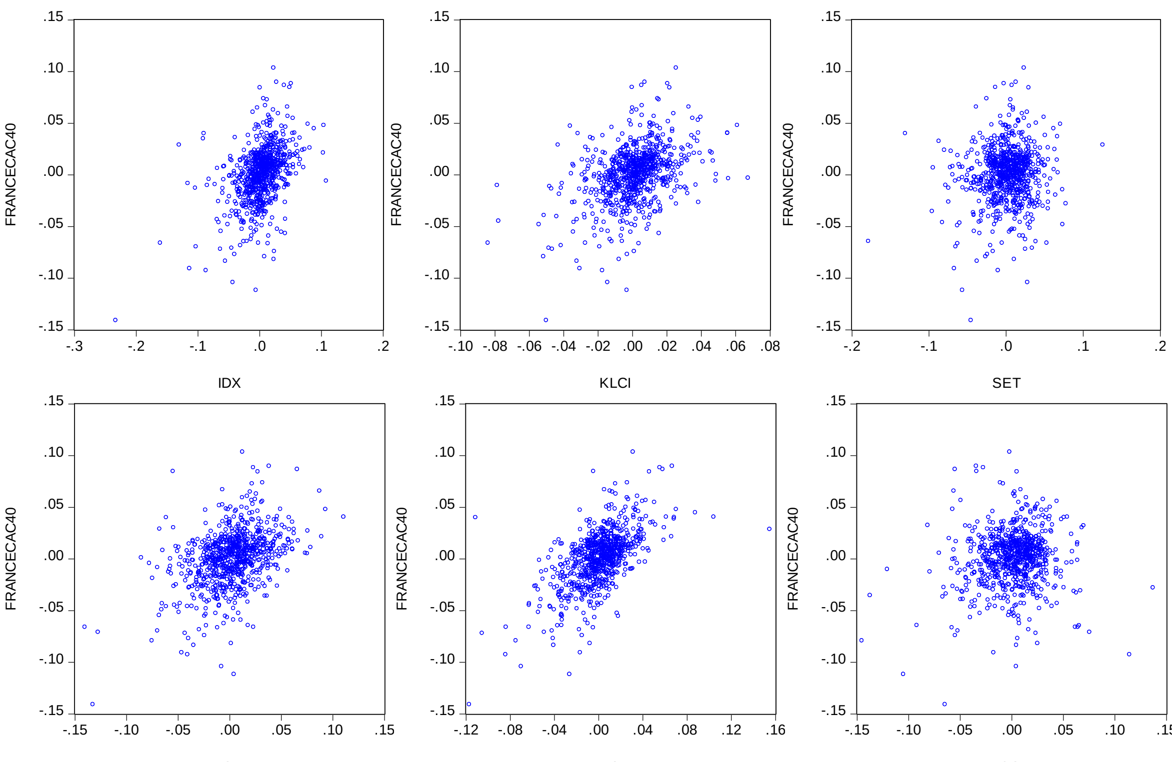
Market Indices Return Scatter Plot: Germany DAX 30 & Emerging Asia



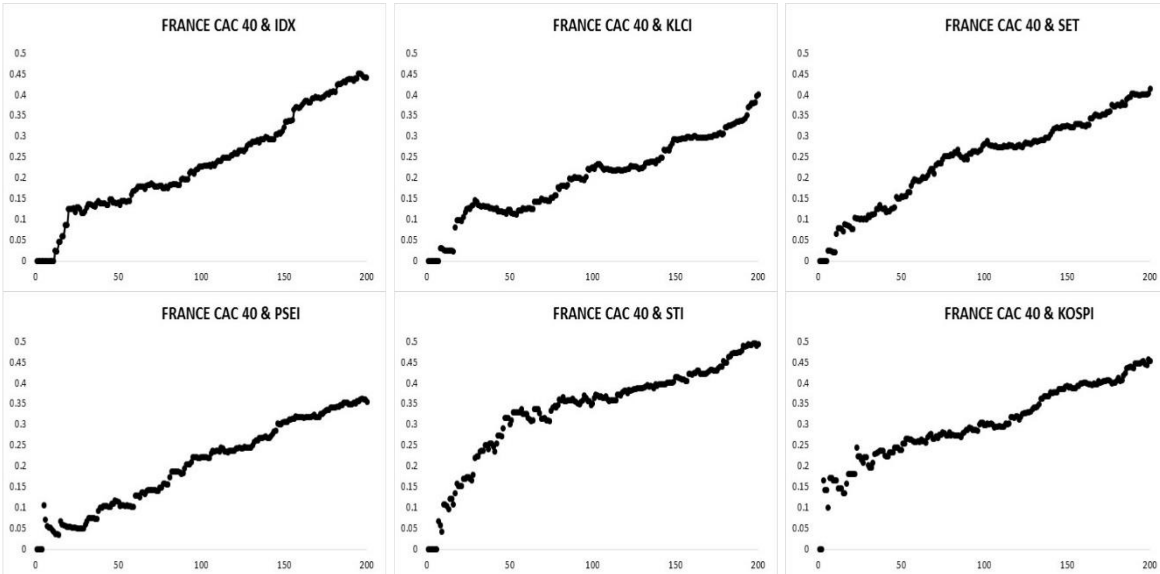
Linkage Estimator Plot: Germany DAX 30 and Emerging Asia Market Returns



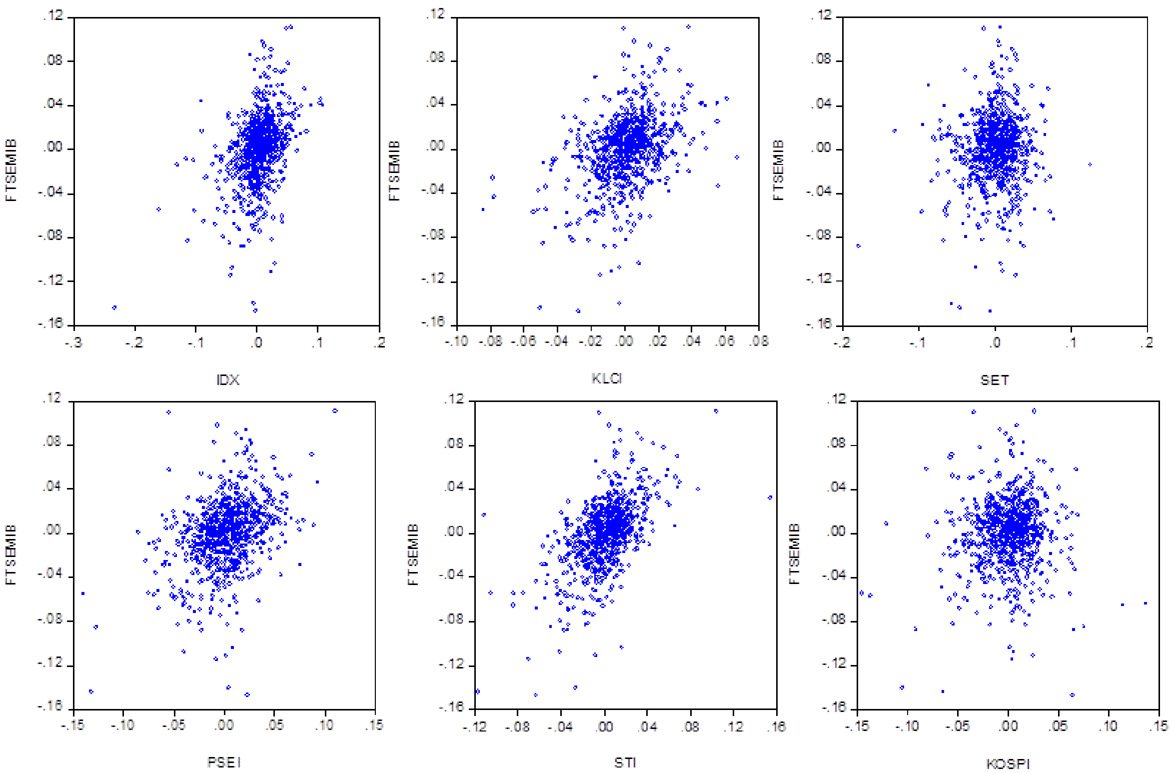
Market Indices Return Scatter Plot: France CAC 40 & Emerging Asia



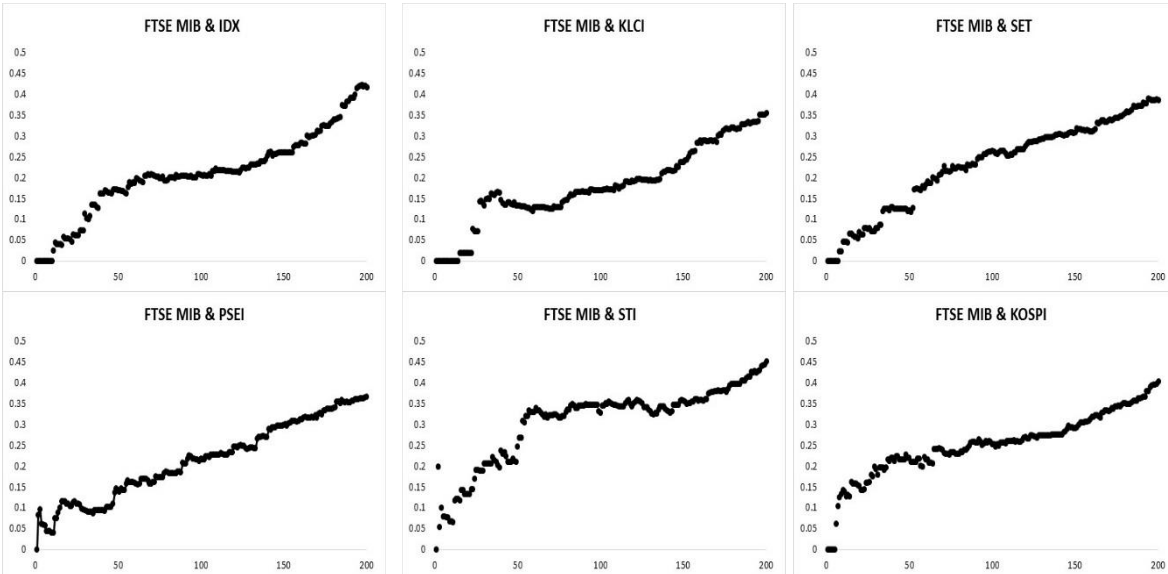
Linkage Estimator Plot: France CAC 40 and Emerging Asia Market Returns



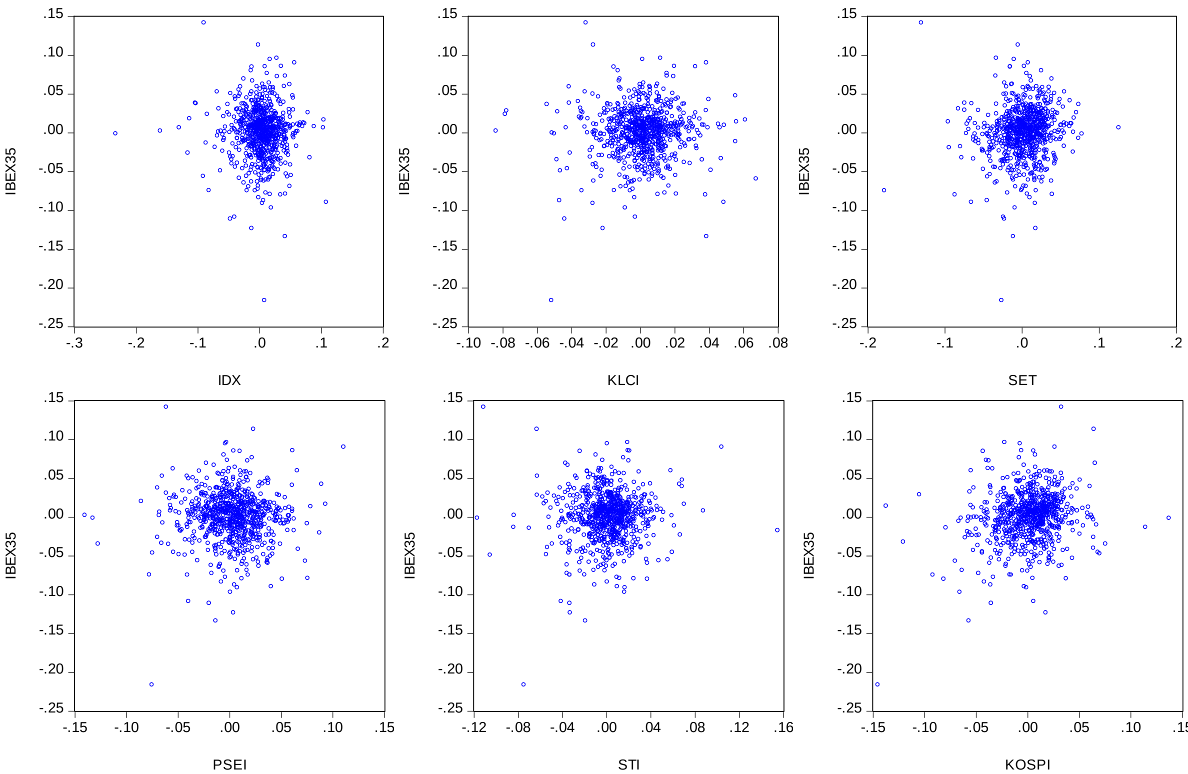
Market Indices Return Scatter Plot: Italy FTSE MIB & Emerging Asia



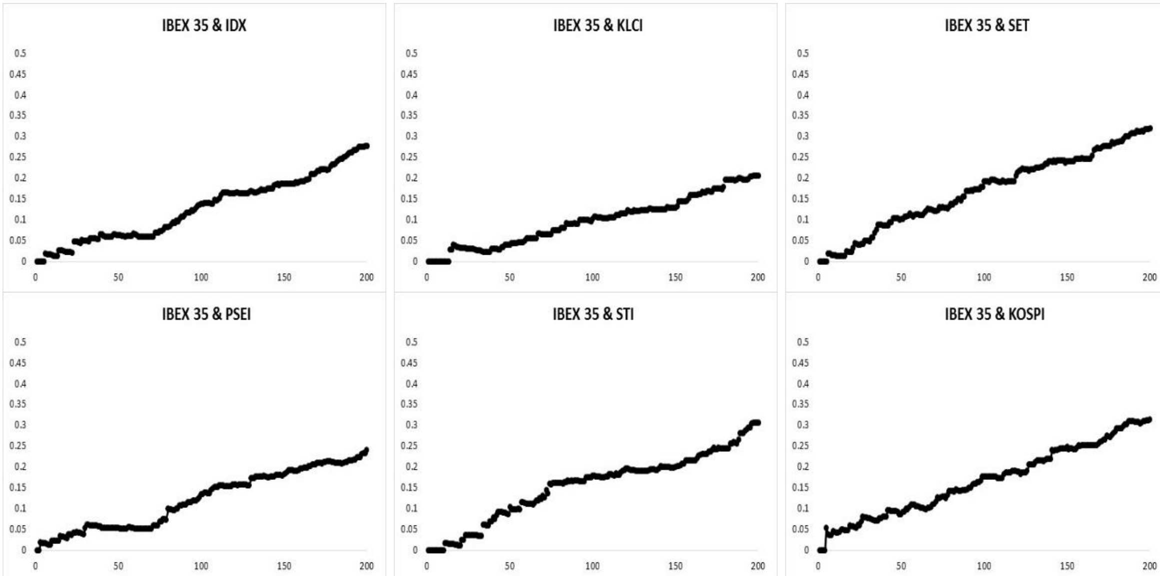
Linkage Estimator Plot: Italy FTSE MIB and Emerging Asia Market Returns



Market Indices Return Scatter Plot: IBEX 35 & Emerging Asia

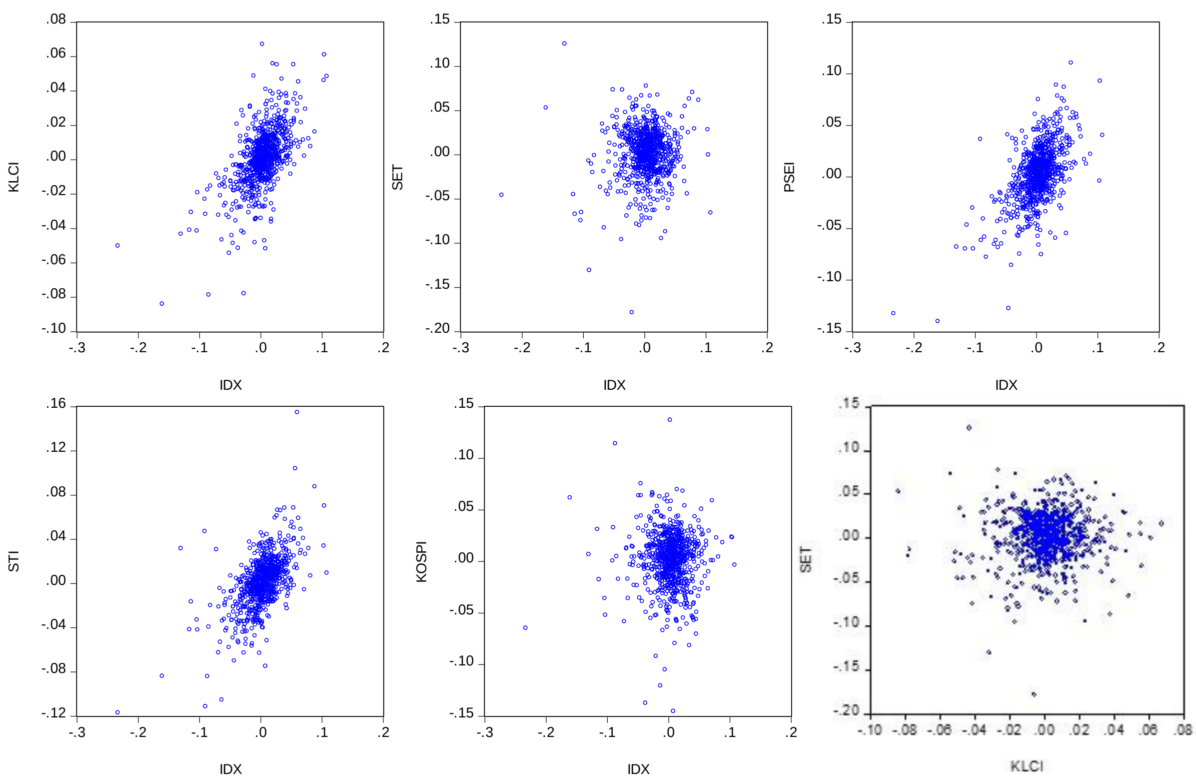


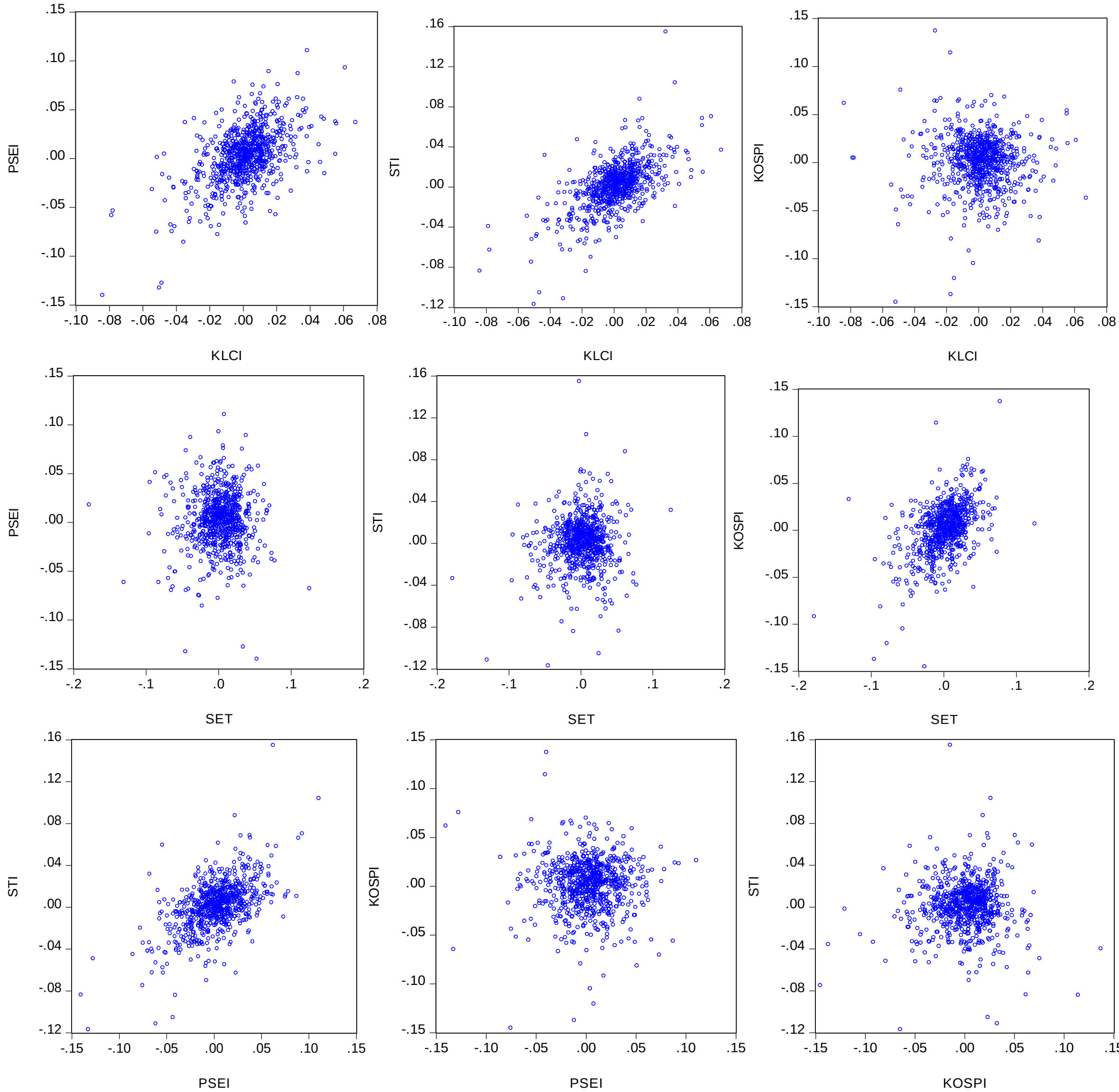
Linkage Estimator Plot: Spain IBEX 35 and Emerging Asia Market Returns



Market Indices Return Scatter Plot: Intraregional Emerging Asia

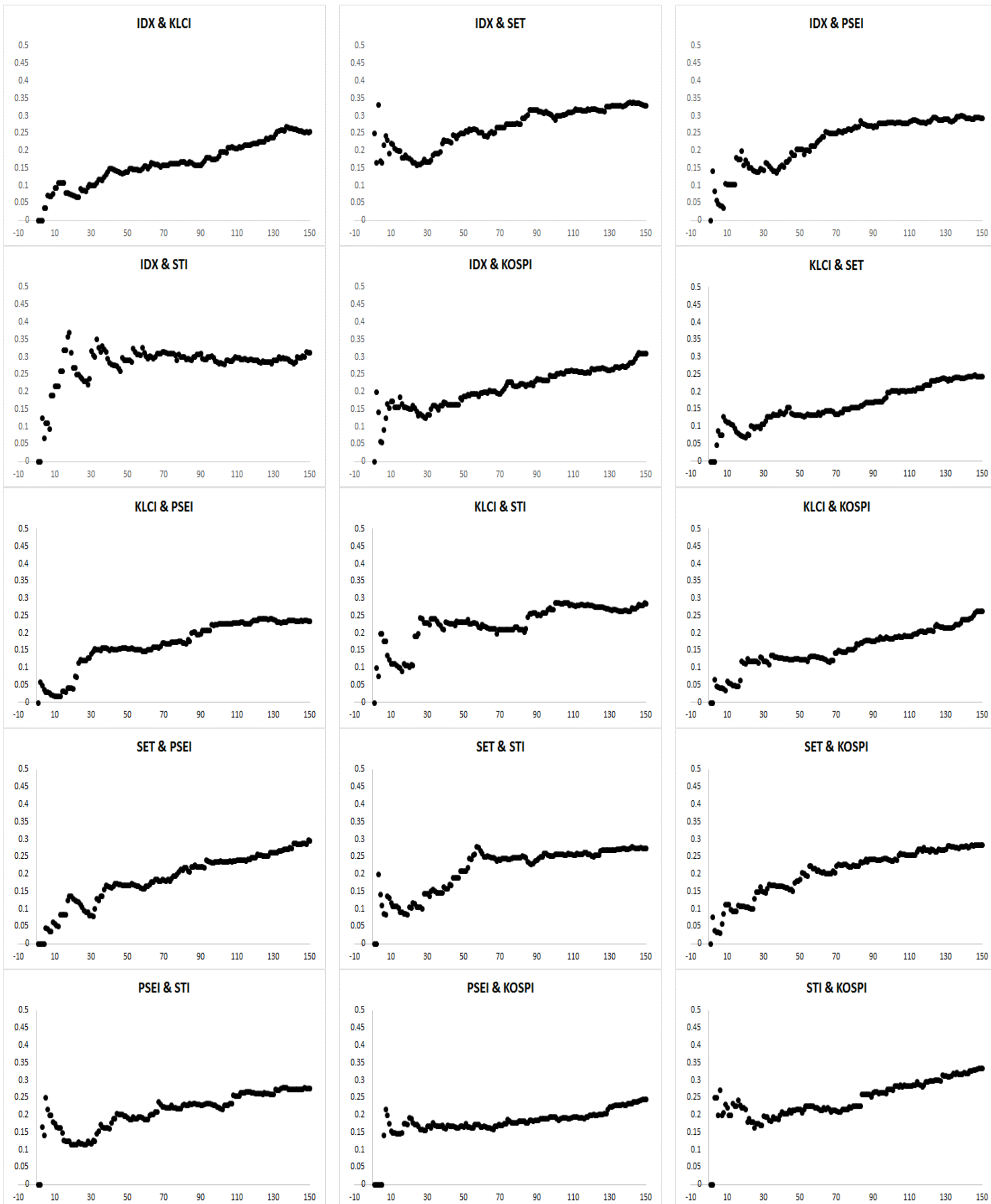
In this part, we provide the scatter plots intraregional Asia market returns that we use in our analysis. We conclude the asymptotic dependency between pairs of market stocks in Table 5 in Chapter 5 part Results and Discussion.




PSEI
KLCI
STI
KLCI
KOSPI
KLCI
PSEI
SET
STI
SET
KOSPI
SET
STI
PSEI
KOSPI
PSEI
STI
KOSPI

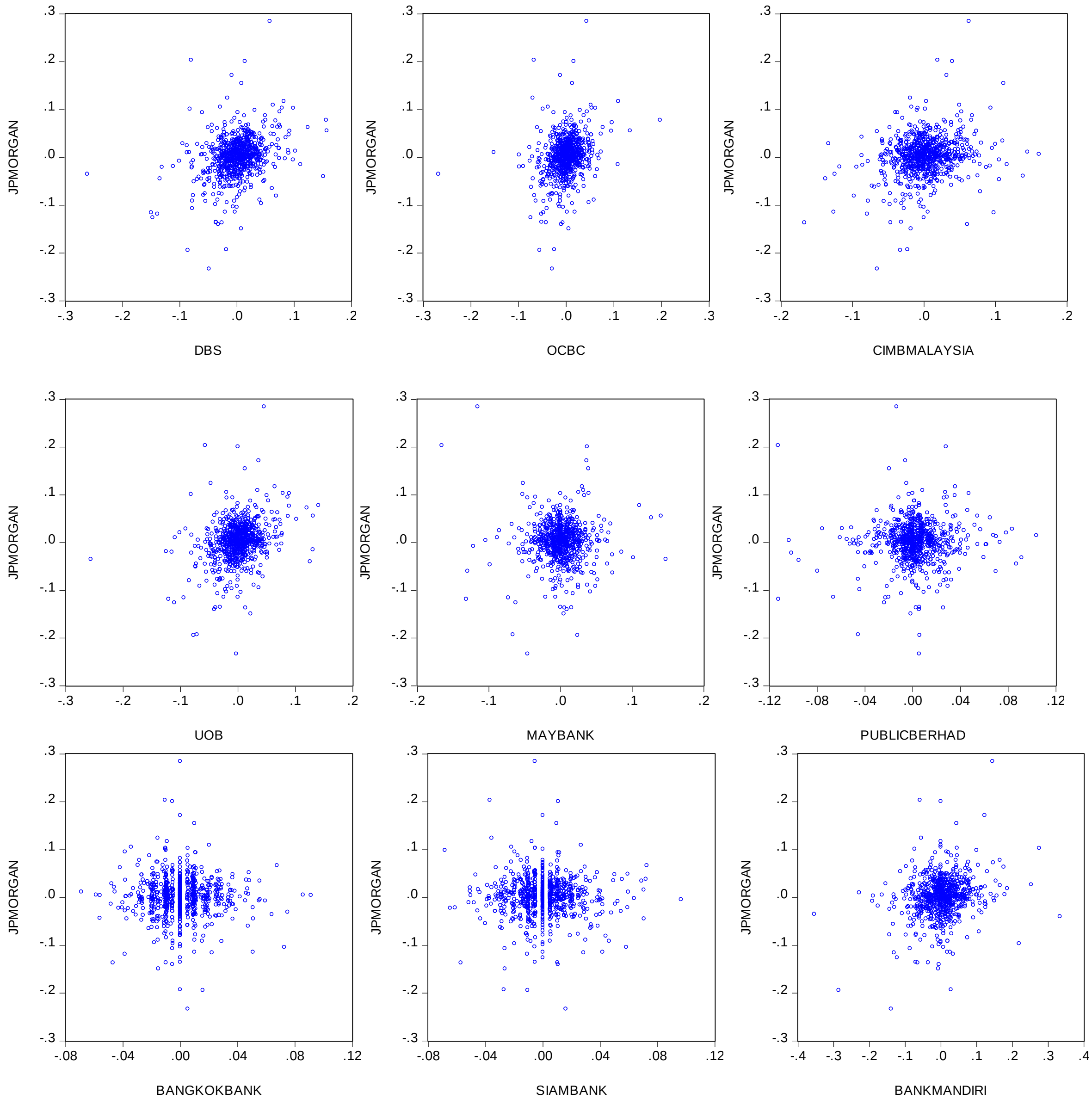
Linkage Estimator Plot of Intra Asia Stock Market Return

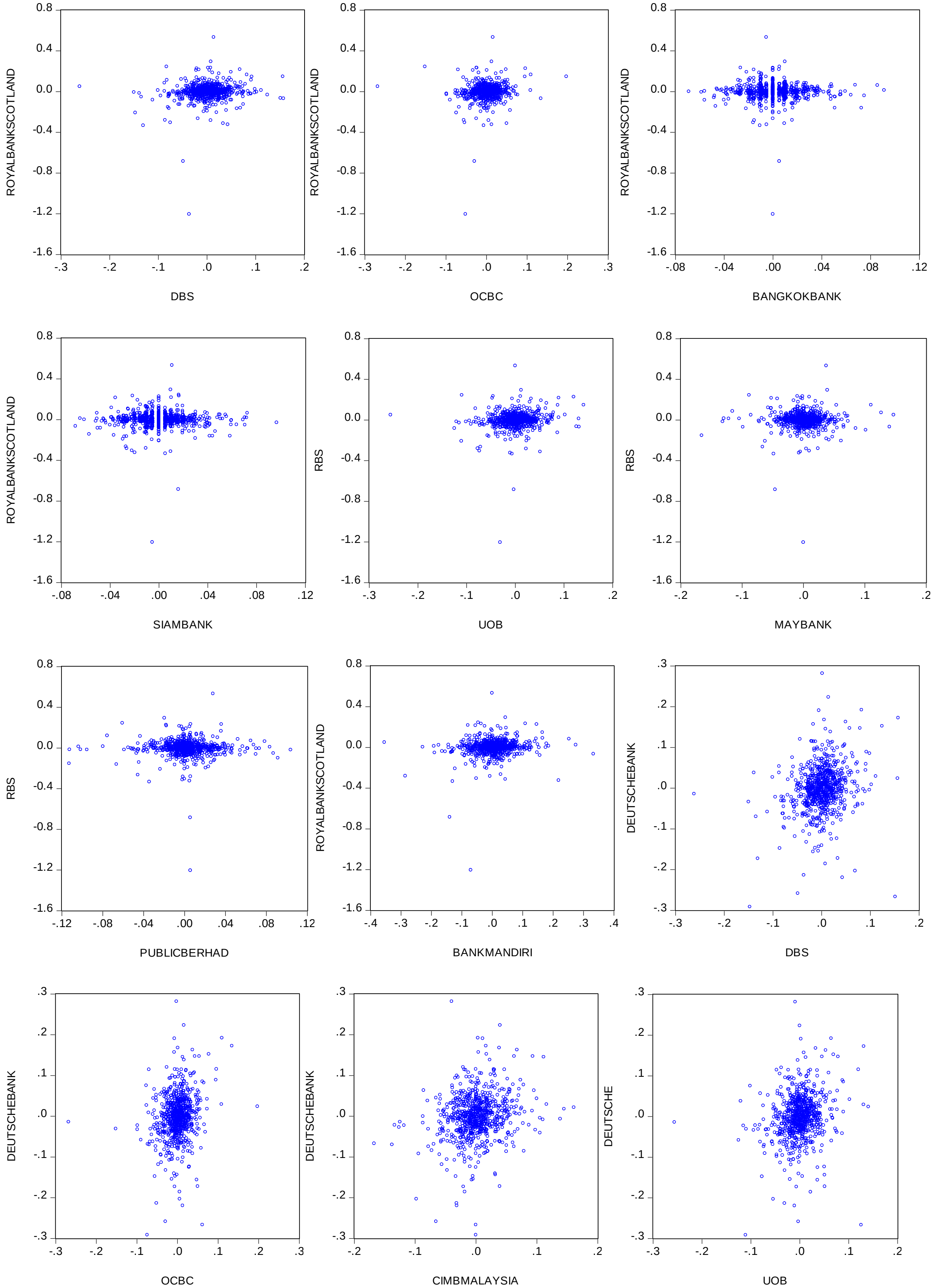
In this part, we provide the linkages estimator plots of Intraregional Asia market returns that we use in our analysis. We conclude the probability of extreme event $E\{k|k \geq 1\}$ in Table 5 in Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.

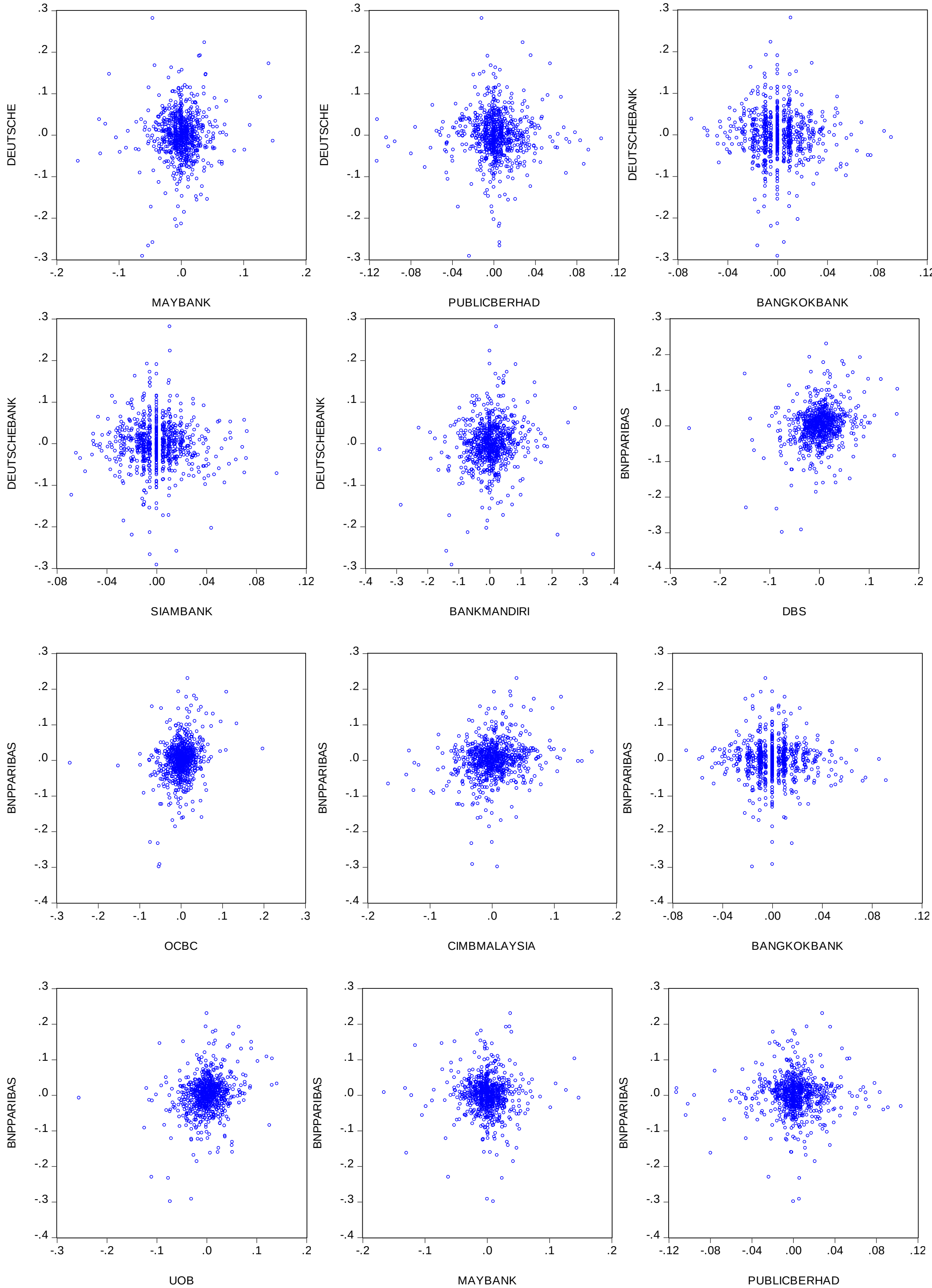


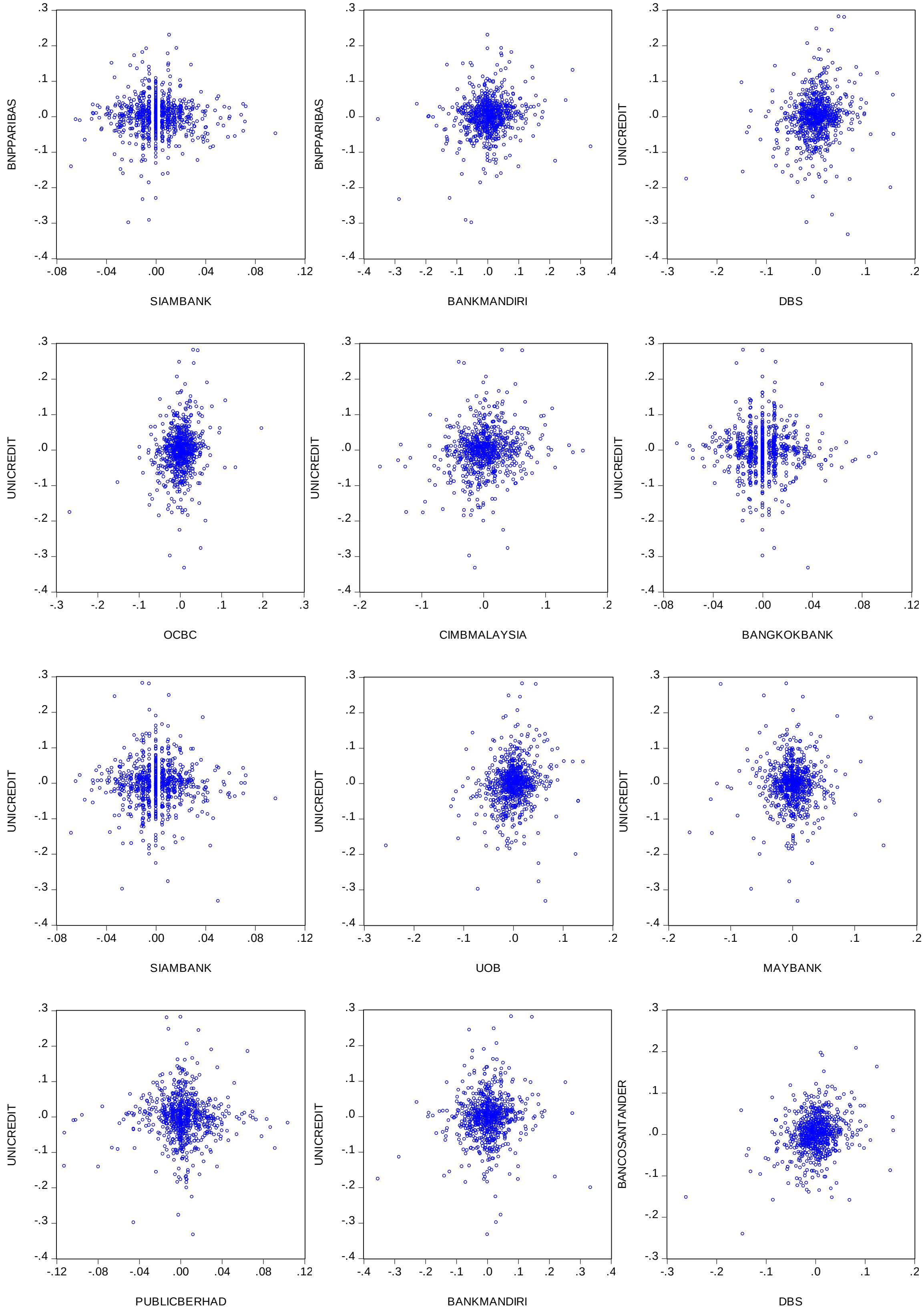
Bank Stock Return Scatter Plot: Crisis Origin Countries and Emerging Asia Countries Banks

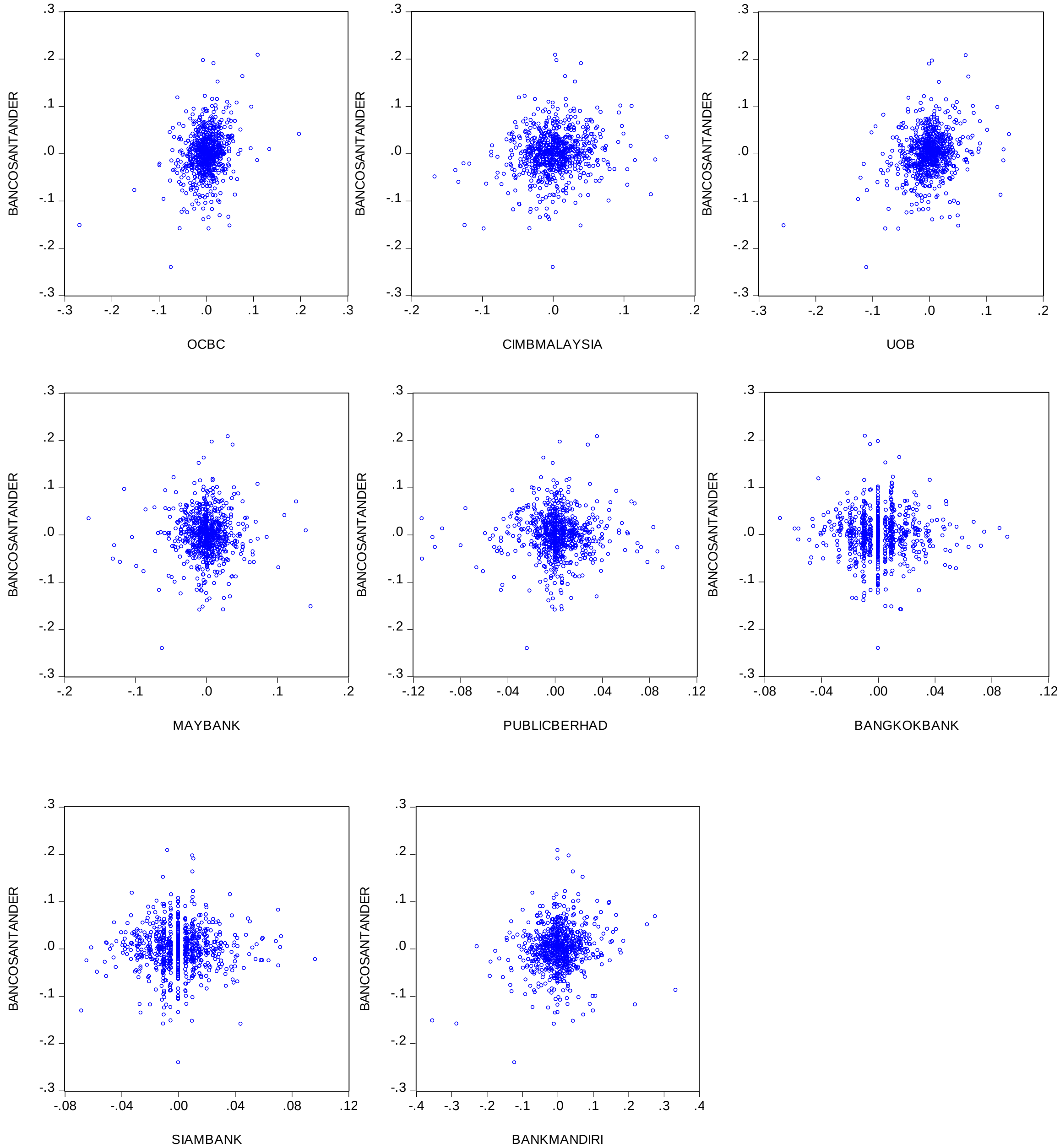
In this part, we provide the scatter plots of bank stock returns from crisis origin countries and emerging Asia countries that we use in our analysis. We conclude the asymptotic dependency between pairs of market stocks in Table 6 in Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.




ROYALBANKSCOTLAND
DBS
ROYALBANKSCOTLAND
OCBC
ROYALBANKSCOTLAND
BANGKOKBANK
ROYALBANKSCOTLAND
SIAMBANK
RBS
UOB
RBS
MAYBANK
RBS
PUBLICBERHAD
ROYALBANKSCOTLAND
BANKMANDIRI
DEUTSCHEBANK
DBS
DEUTSCHEBANK
OCBC
DEUTSCHEBANK
CIMBMALAYSIA
DEUTSCHE
UOB

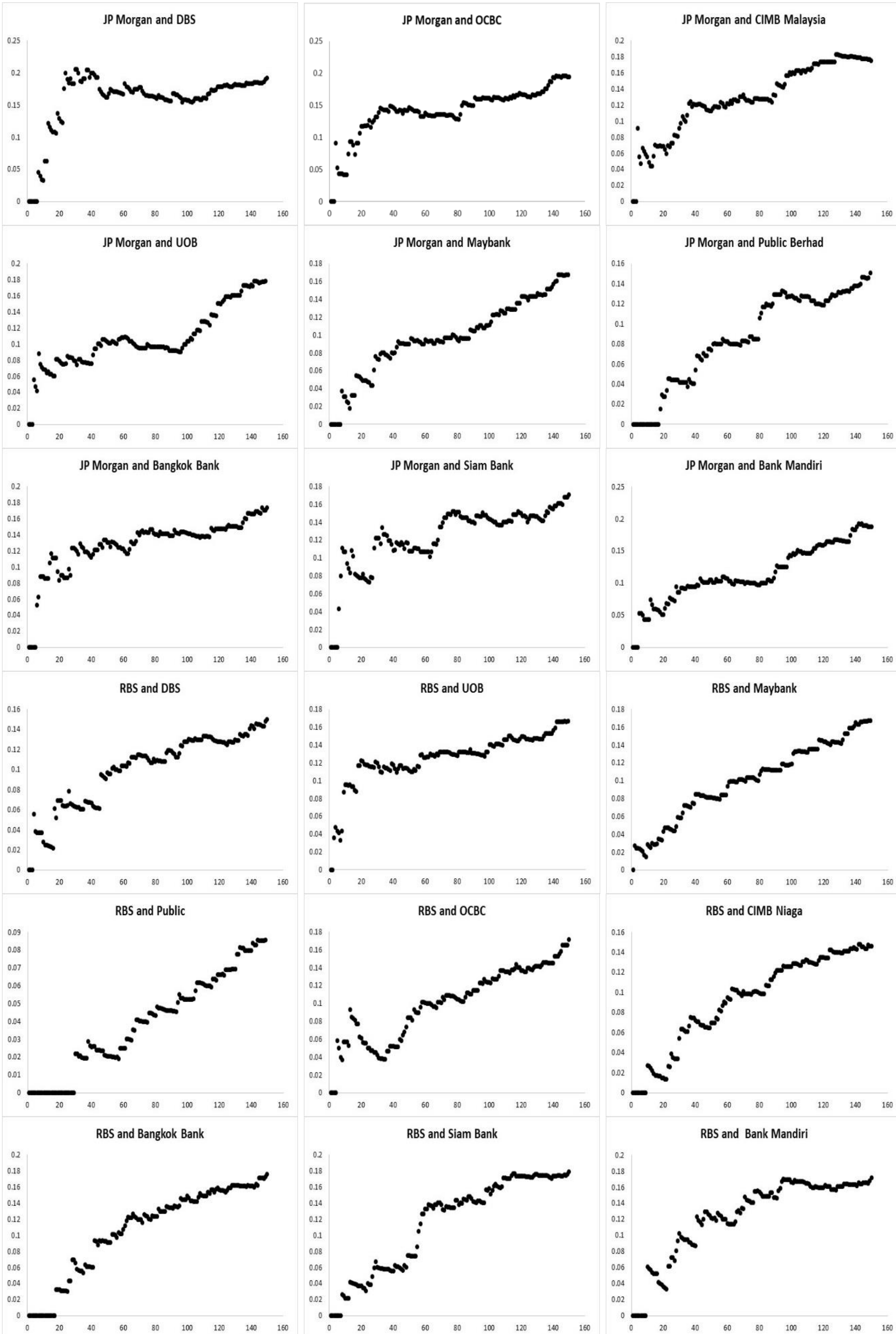

DEUTSCHE
MAYBANK
DEUTSCHE
PUBLICBERHAD
DEUTSCHEBANK
BANGKOKBANK
DEUTSCHEBANK
SIAMBANK
DEUTSCHEBANK
BANKMANDIRI
BNPPARIBAS
DBS
BNPPARIBAS
OCBC
BNPPARIBAS
CIMBMALAYSIA
BNPPARIBAS
BANGKOKBANK
BNPPARIBAS
UOB
BNPPARIBAS
MAYBANK
BNPPARIBAS
PUBLICBERHAD

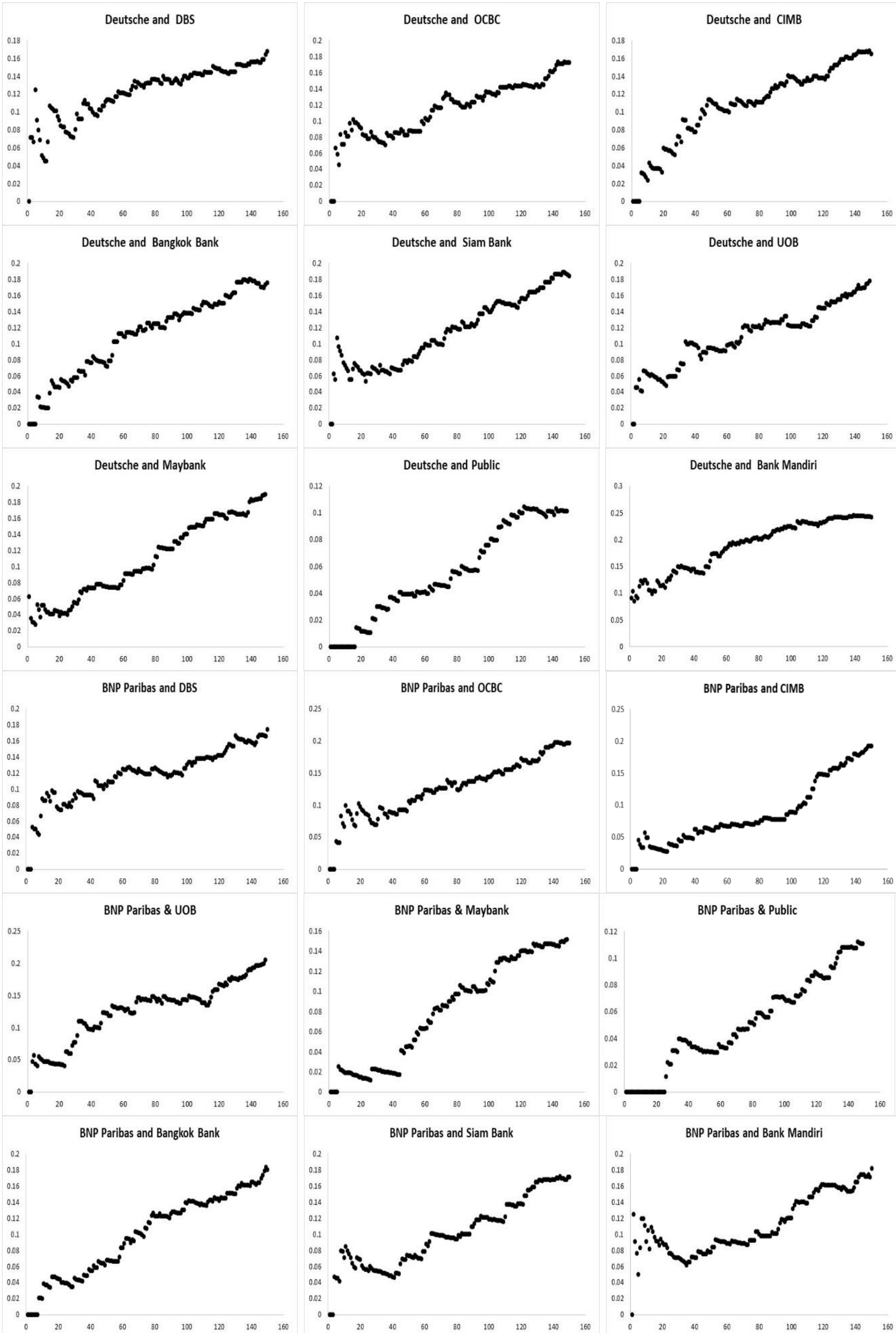

BNPPARIBAS
SIAMBANK
BNPPARIBAS
BANKMANDIRI
UNICREDIT
DBS
UNICREDIT
OCBC
UNICREDIT
CIMBMALAYSIA
UNICREDIT
BANGKOKBANK
UNICREDIT
SIAMBANK
UNICREDIT
UOB
UNICREDIT
MAYBANK
UNICREDIT
PUBLICBERHAD
UNICREDIT
BANKMANDIRI
BANCOSANTANDER
DBS

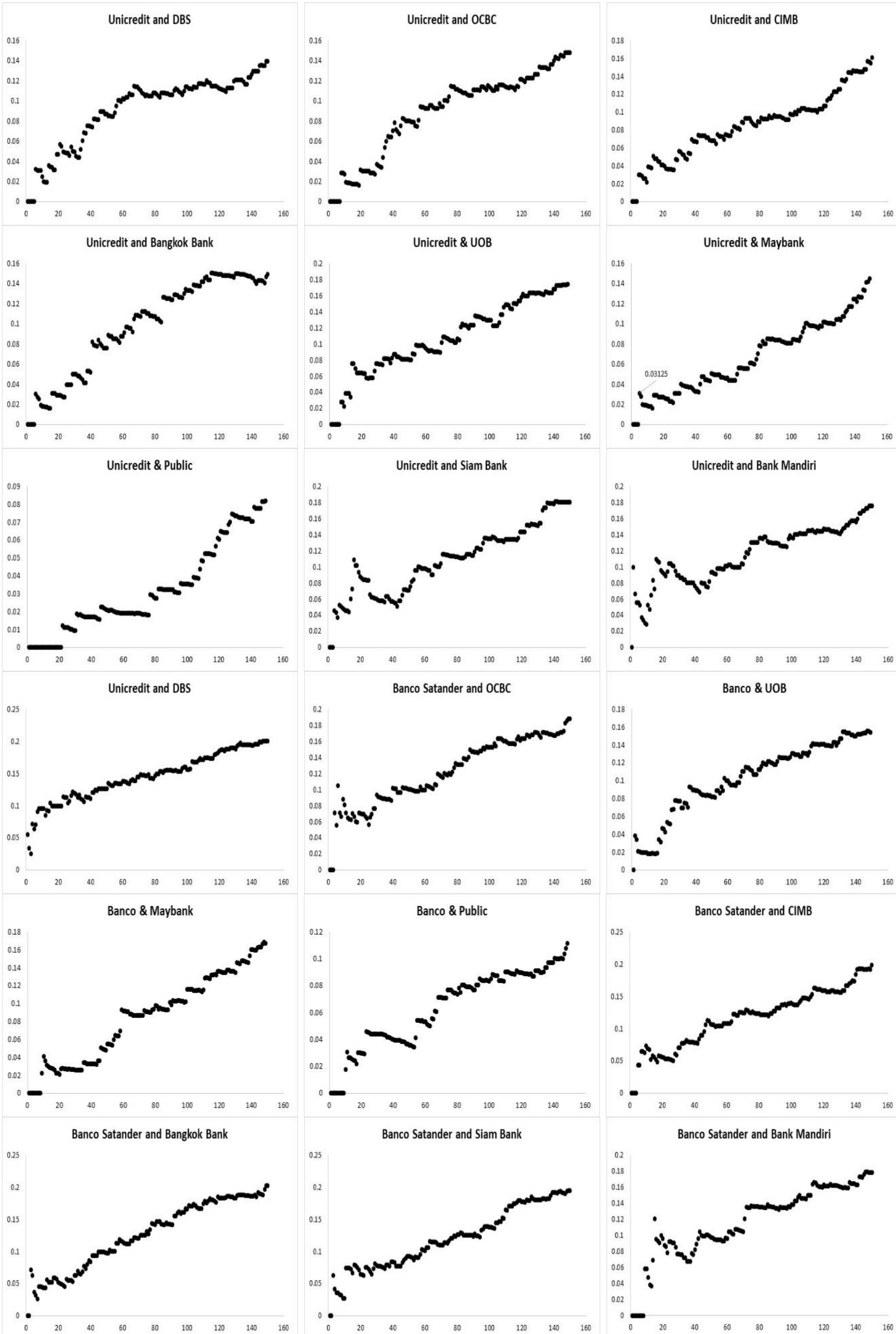


Linkage Estimator Plot Bank Crisis Origin and Emerging Asia Countries

In this part, we provide the linkages estimator plots of bank stock returns from crisis origin countries and emerging Asia countries that we use in our analysis. We conclude the probability of extreme event $E\{k|k\geq 1\}$ in Table 6 in Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.

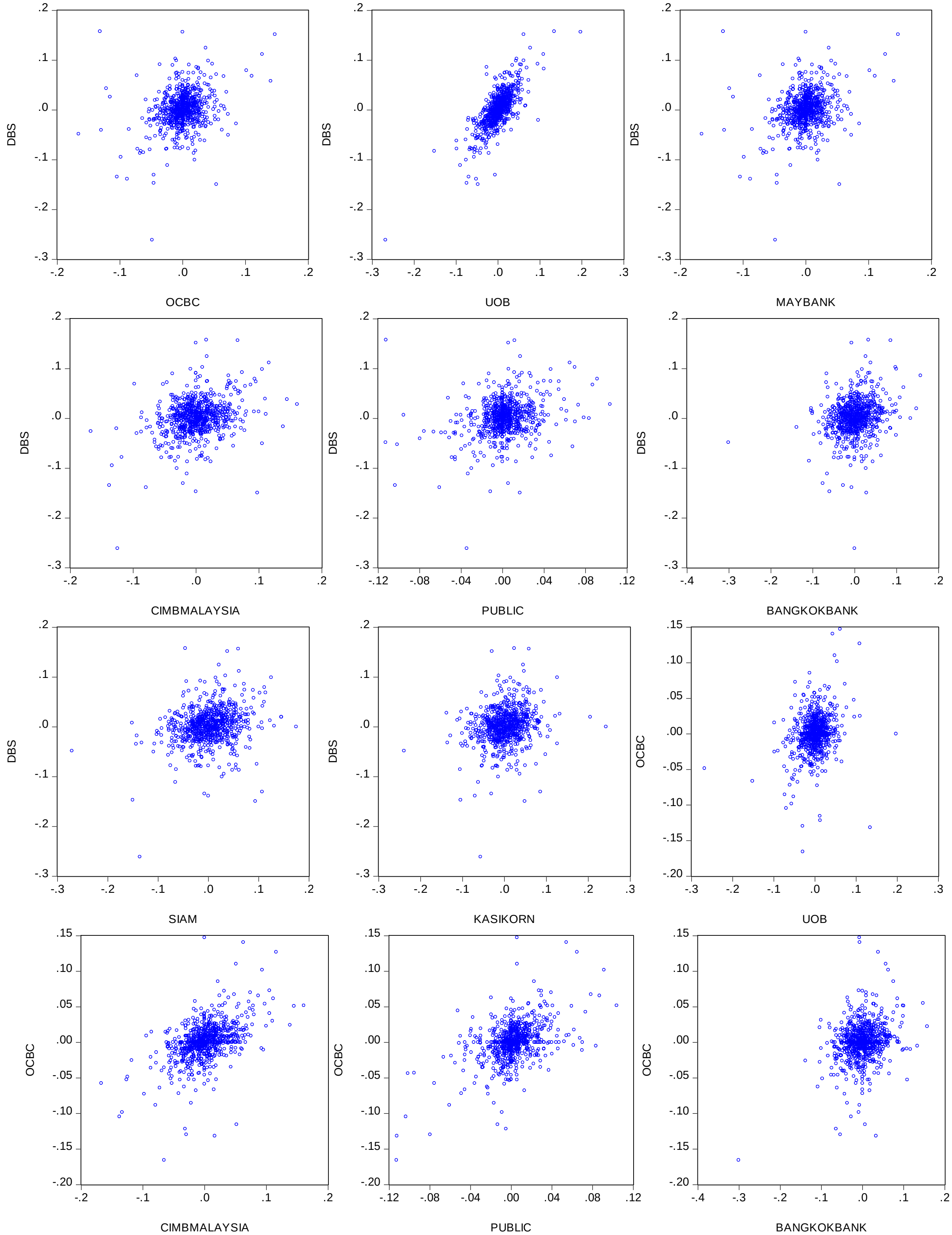

JP Morgan and DBS
JP Morgan and OCBC
JP Morgan and CIMB Malaysia
JP Morgan and UOB
JP Morgan and Maybank
JP Morgan and Public Berhad
JP Morgan and Bangkok Bank
JP Morgan and Siam Bank
JP Morgan and Bank Mandiri
RBS and DBS
RBS and UOB
RBS and Maybank
RBS and Public
RBS and OCBC
RBS and CIMB Niaga
RBS and Bangkok Bank
RBS and Siam Bank
RBS and Bank Mandiri

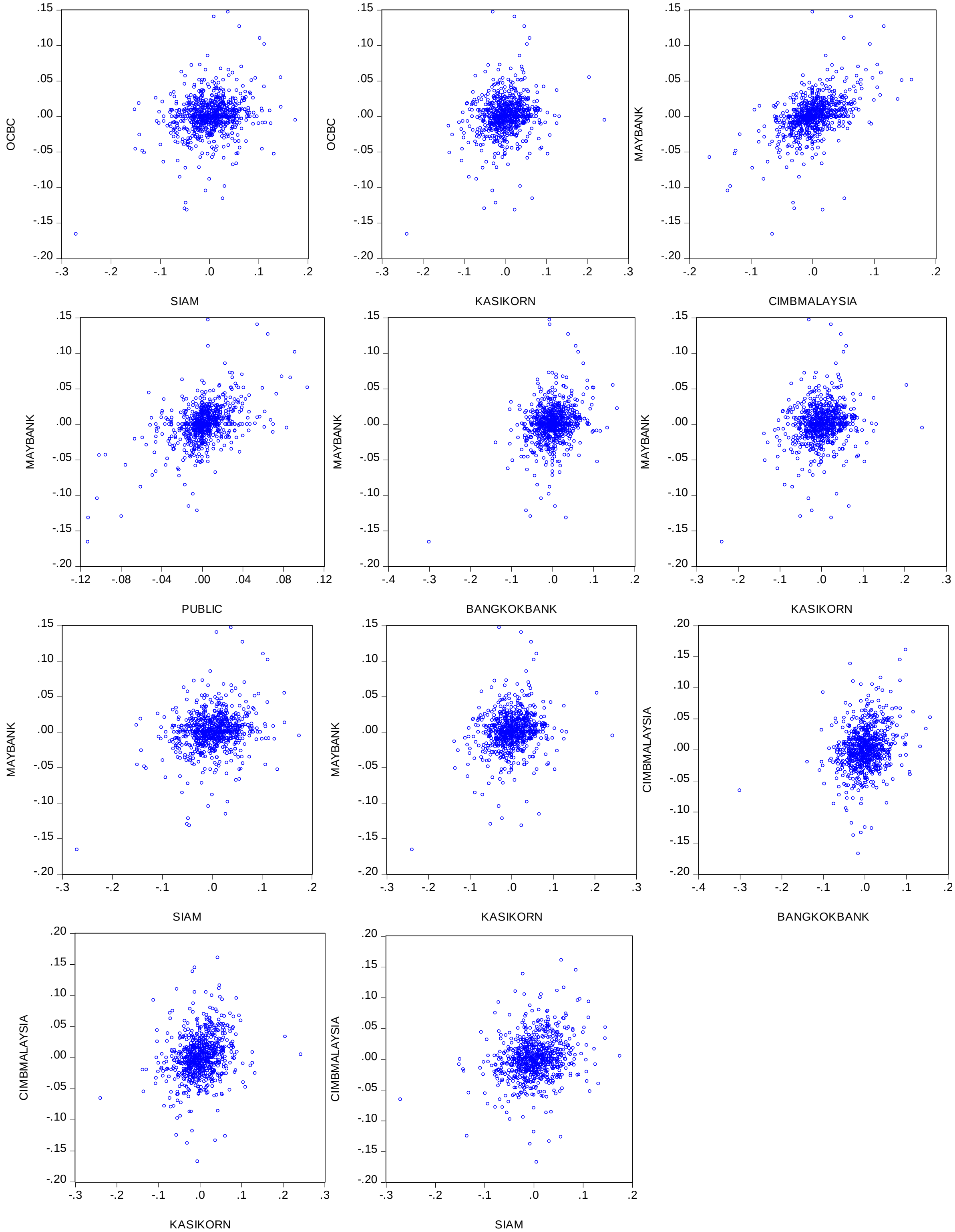

Deutsche and DBS
Deutsche and OCBC
Deutsche and CIMB
Deutsche and Bangkok Bank
Deutsche and Siam Bank
Deutsche and UOB
Deutsche and Maybank
Deutsche and Public
Deutsche and Bank Mandiri
BNP Paribas and DBS
BNP Paribas and OCBC
BNP Paribas and CIMB
BNP Paribas & UOB
BNP Paribas & Maybank
BNP Paribas & Public
BNP Paribas and Bangkok Bank
BNP Paribas and Siam Bank
BNP Paribas and Bank Mandiri


Unicredit and DBS
Unicredit and OCBC
Unicredit and CIMB
Unicredit and Bangkok Bank
Unicredit & UOB
Unicredit & Maybank
0.03125
Unicredit & Public
Unicredit and Siam Bank
Unicredit and Bank Mandiri
Unicredit and DBS
Banco Satander and OCBC
Banco & UOB
Banco & Maybank
Banco & Public
Banco Satander and CIMB
Banco Satander and Bangkok Bank
Banco Satander and Siam Bank
Banco Satander and Bank Mandiri

Bank Stocks Return Scatter Plot: Intraregional Emerging Asia

In this part, we provide the scatter plots of some pairs of emerging Asia bank stock returns that we use in our analysis. We conclude the asymptotic dependency between pairs of market stocks in Table 7 in the Chapter 5 part Results and Discussion.

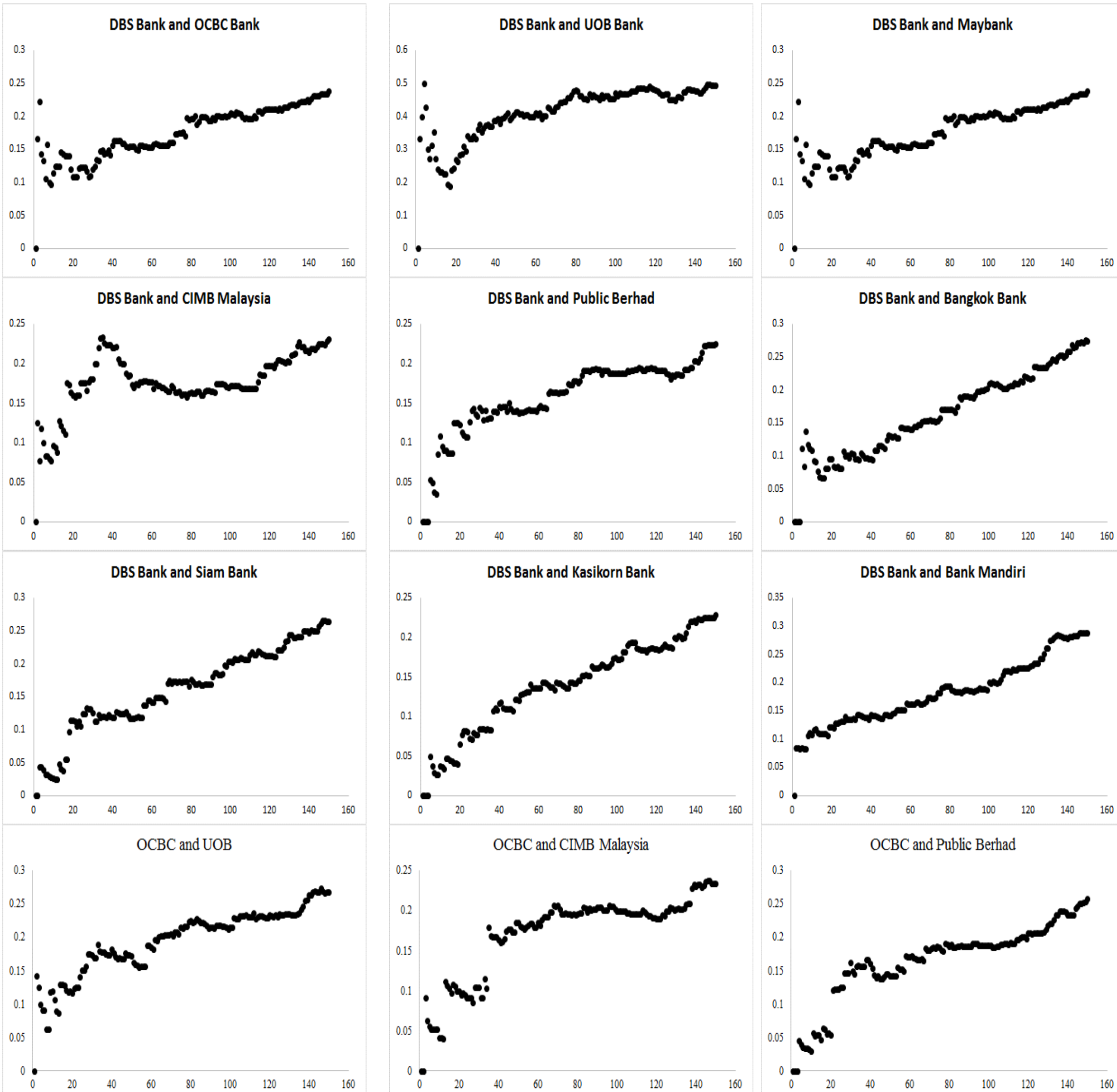


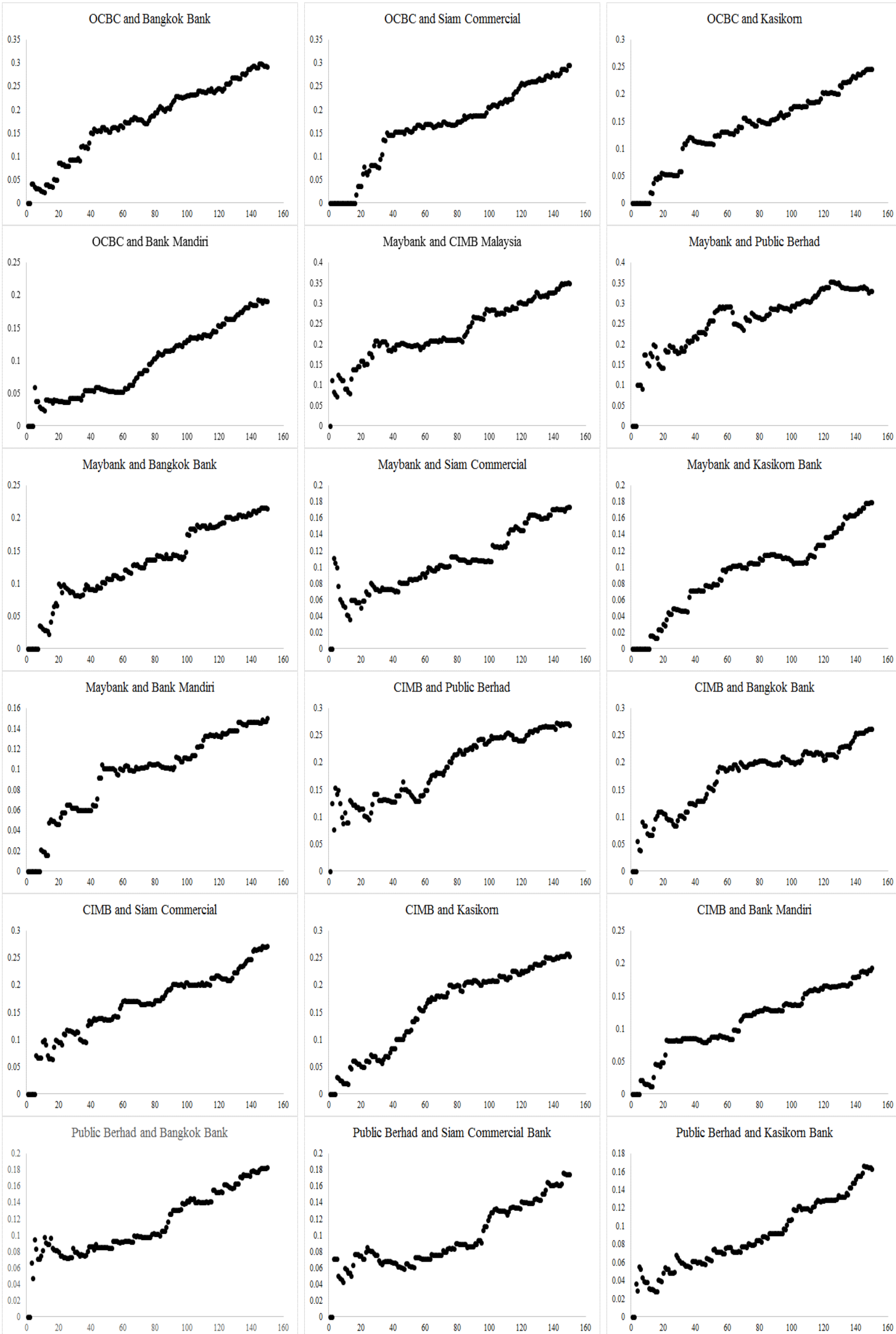


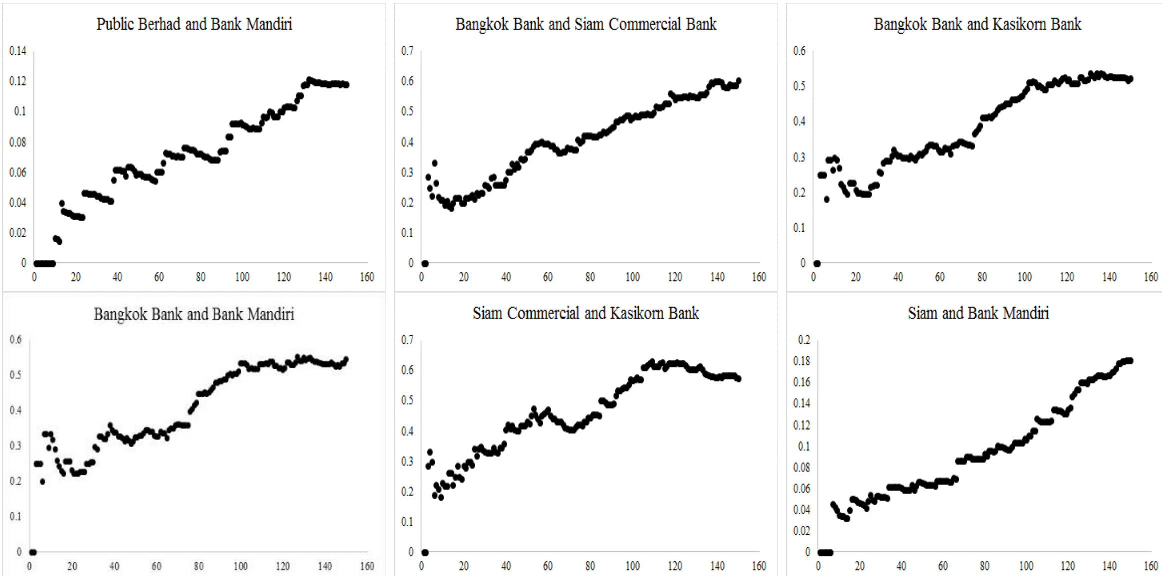
Linkage Estimator Plot Intra Asia Bank Stock Return

In this part, we provide the linkages estimator plots of emerging Asia bank stock returns that we use in our analysis. We conclude the probability of extreme event $E\{k|k\geq 1\}$ in several Tables in

Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.



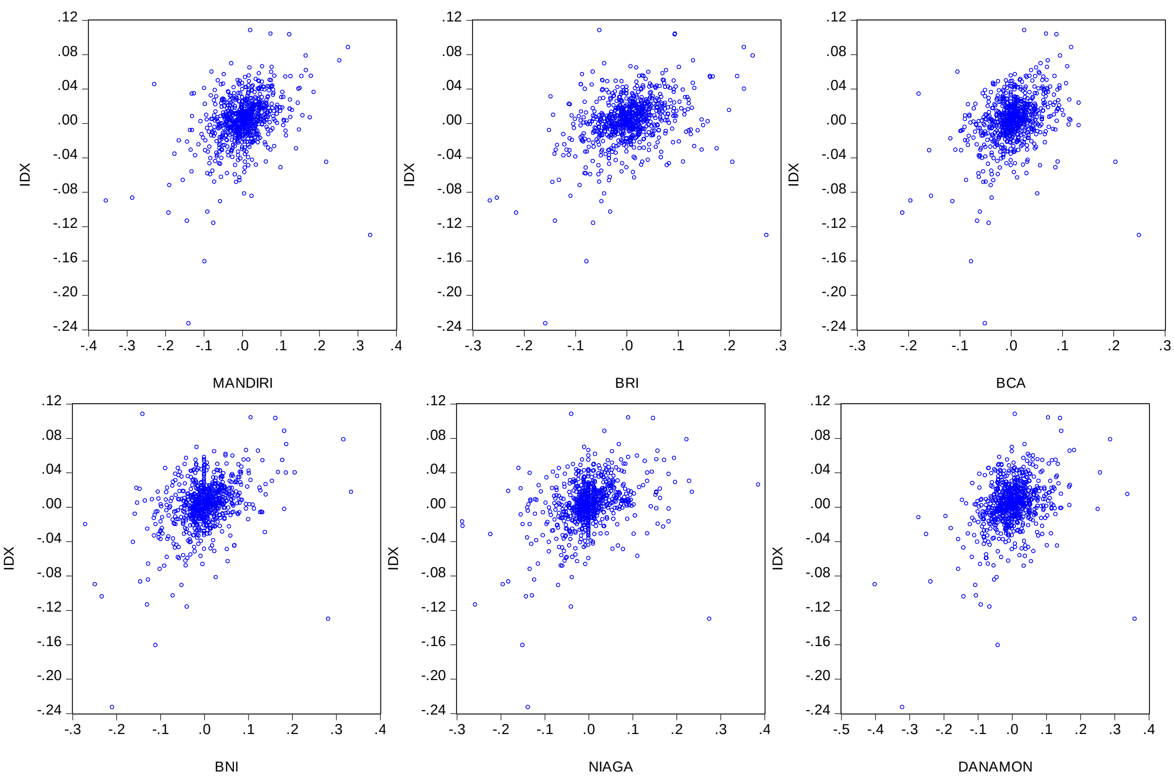

OCBC and Bangkok Bank
OCBC and Siam Commercial
OCBC and Kasikorn
OCBC and Bank Mandiri
Maybank and CIMB Malaysia
Maybank and Public Berhad
Maybank and Bangkok Bank
Maybank and Siam Commercial
Maybank and Kasikorn Bank
Maybank and Bank Mandiri
CIMB and Public Berhad
CIMB and Bangkok Bank
CIMB and Siam Commercial
CIMB and Kasikorn
CIMB and Bank Mandiri
Public Berhad and Bangkok Bank
Public Berhad and Siam Commercial Bank
Public Berhad and Kasikorn Bank

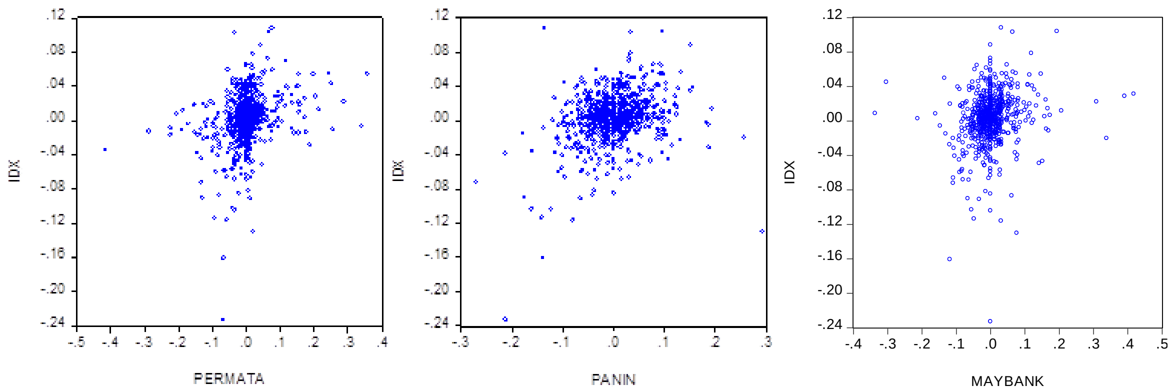


Market and Bank Stock Return Scatter Plot

Indonesia

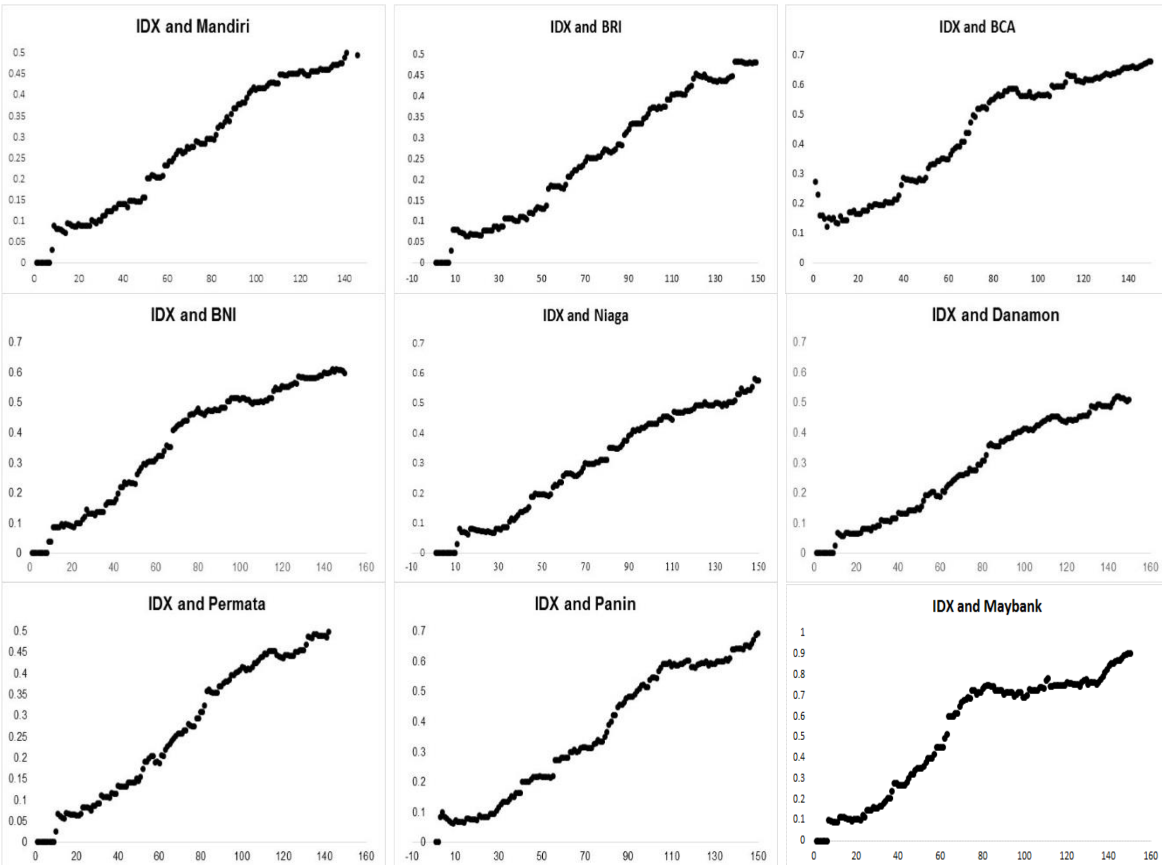
In this part, we provide the scatter plots of some pairs of emerging Asia market stock and bank stock returns that we use in our analysis. We conclude the asymptotic dependency between pairs of bank stock returns in Table 8 in the Chapter 5 part Results and Discussion.



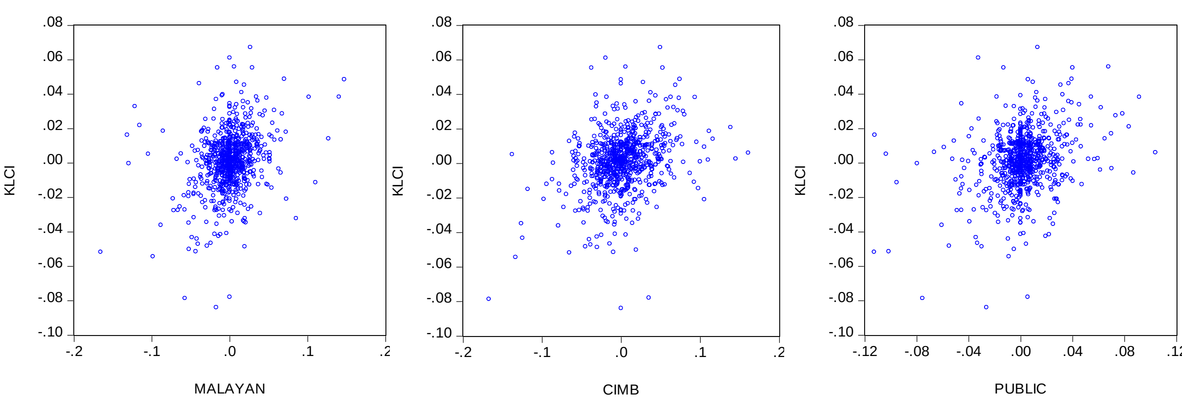

IDX
PERMATA
PANIN
MAYBANK

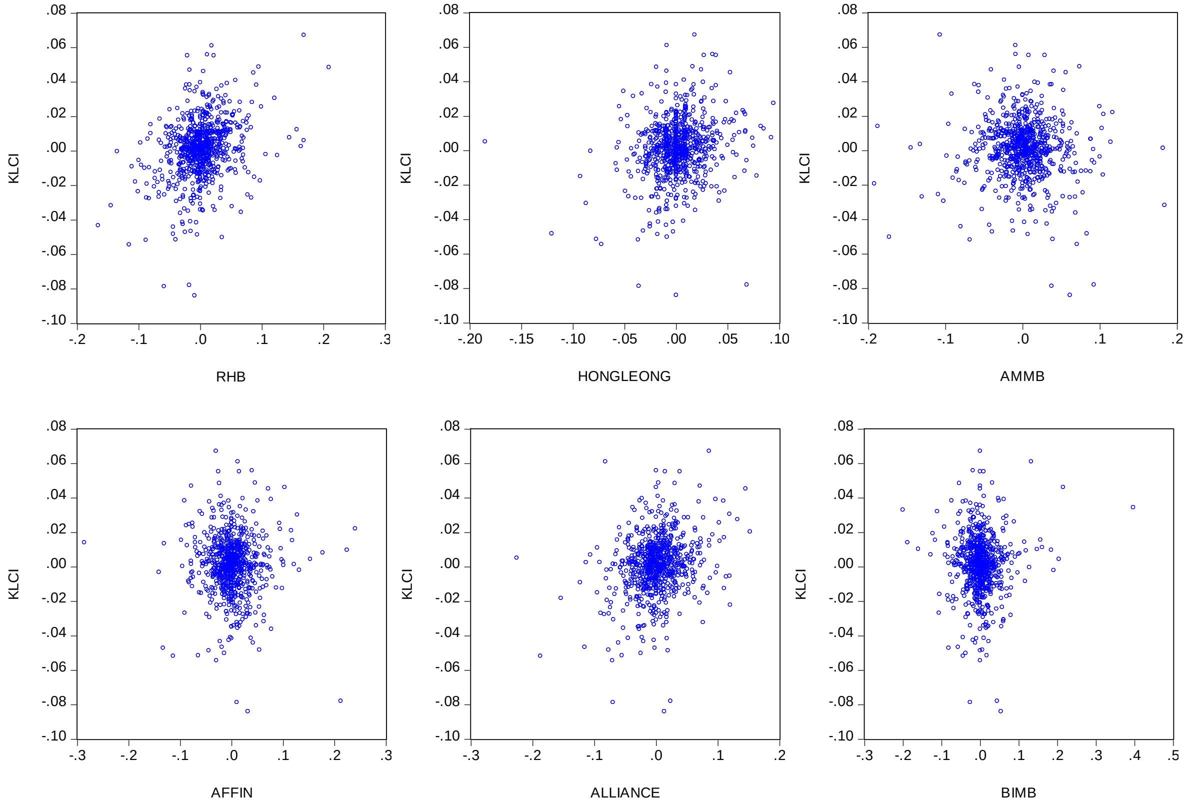
Linkage Estimator Plot: IDX and Indonesian Bank Stock Returns

In this part, we provide the linkages estimator plots of emerging Asia bank stock returns that we use in our analysis. We conclude the probability of extreme event $E\{k|k\geq 1\}$ in Table 8 in the Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.

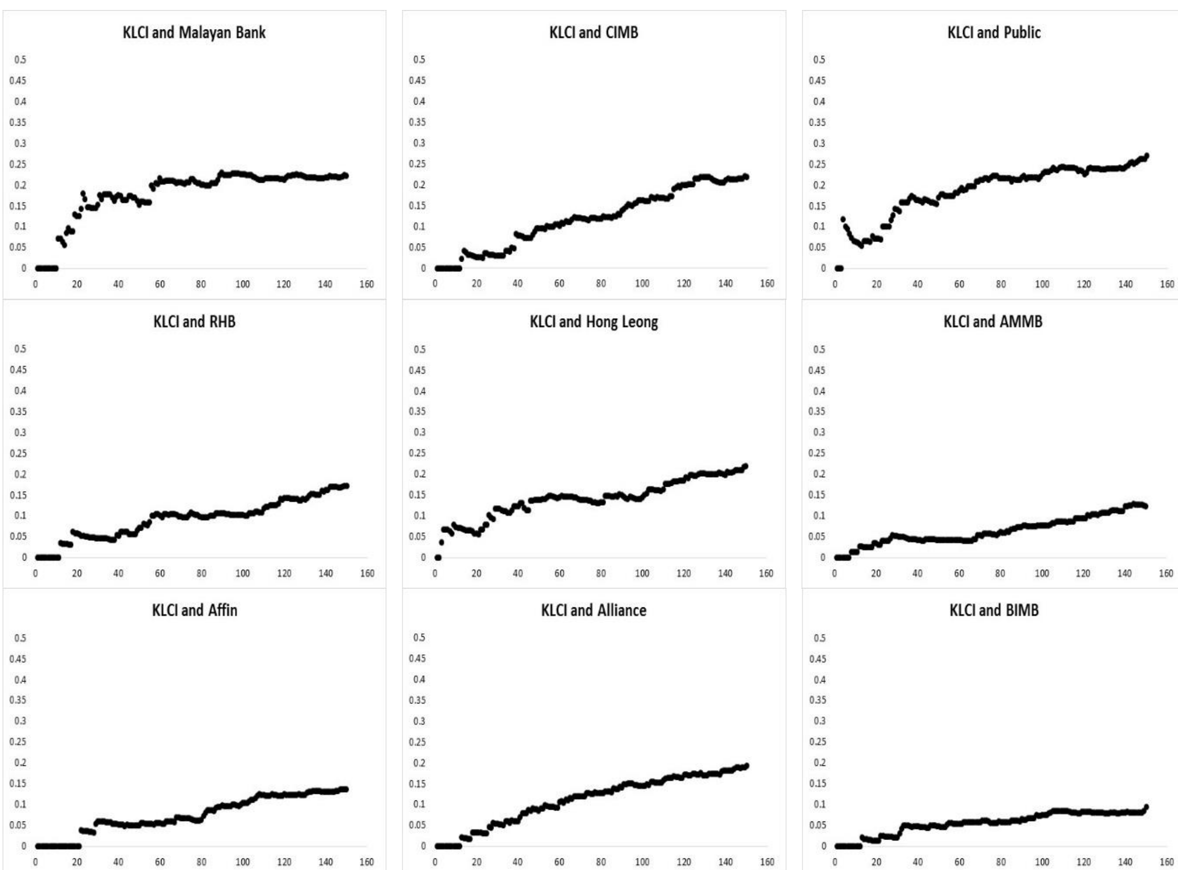


Scatter Plot Malaysia Market and Bank Stock Return

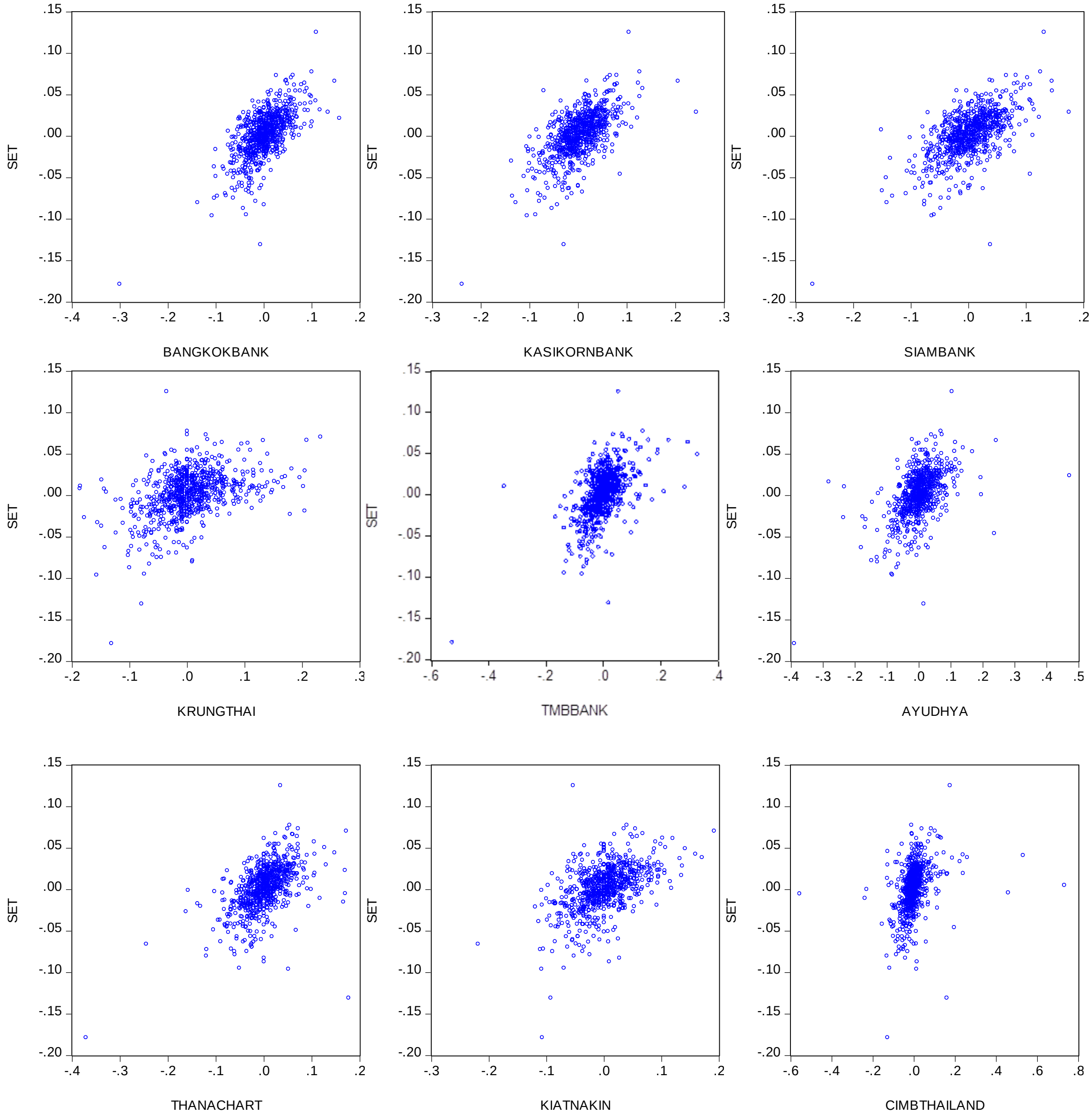




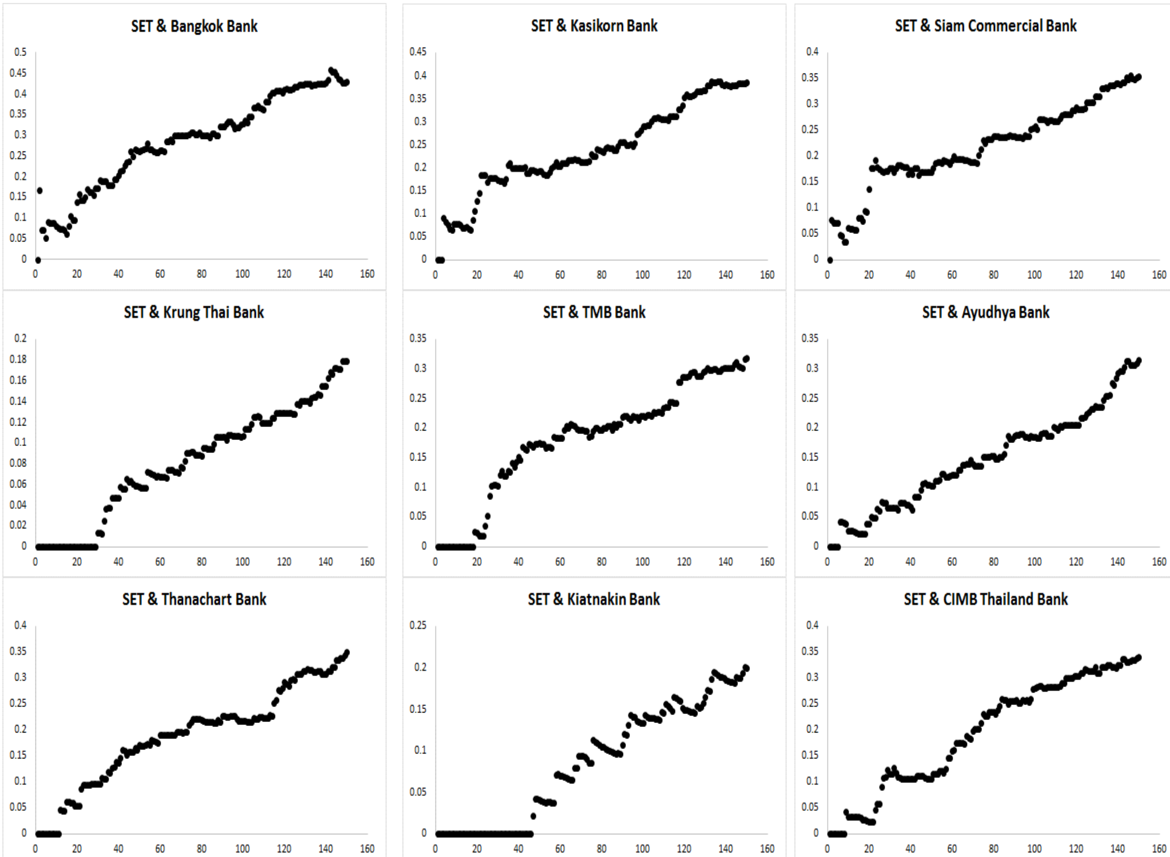
Linkage Estimator Plot: KLCI Market Return and Malaysian Bank Stock Returns



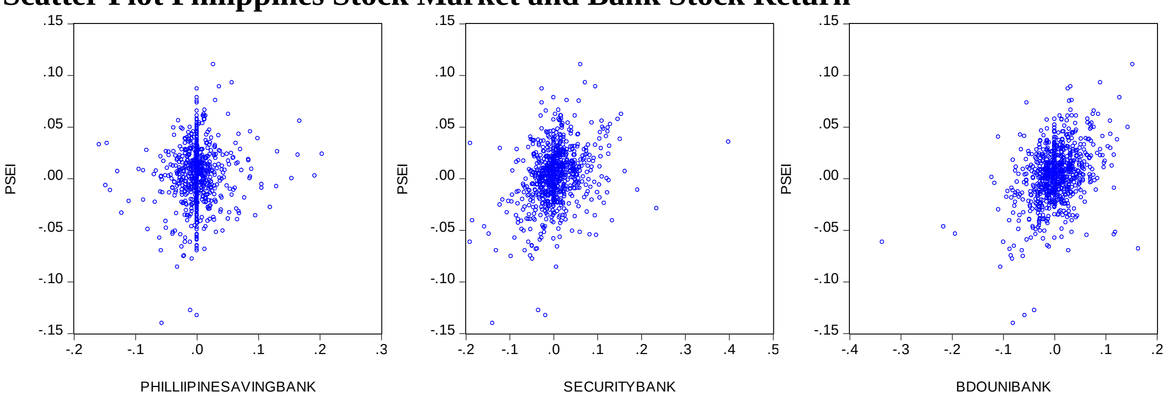
Scatter Plot Thailand Market Return

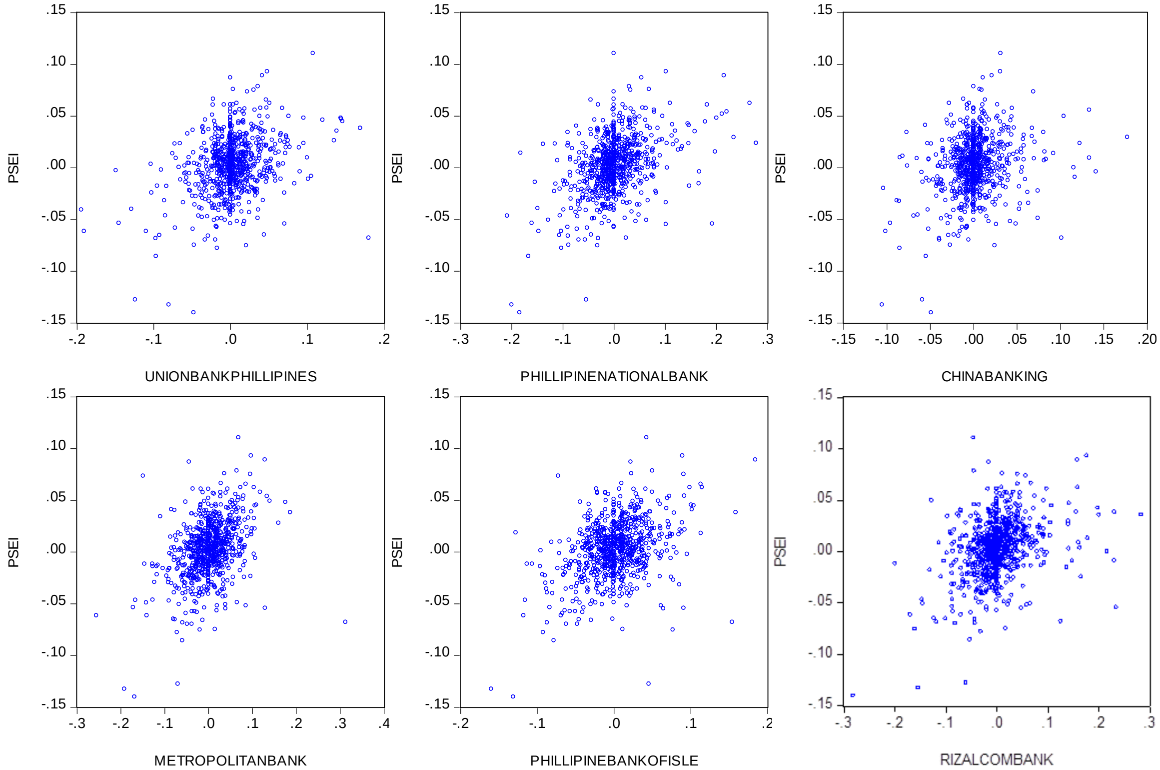


Tail Plot Market Return: SET and Thailand Bank

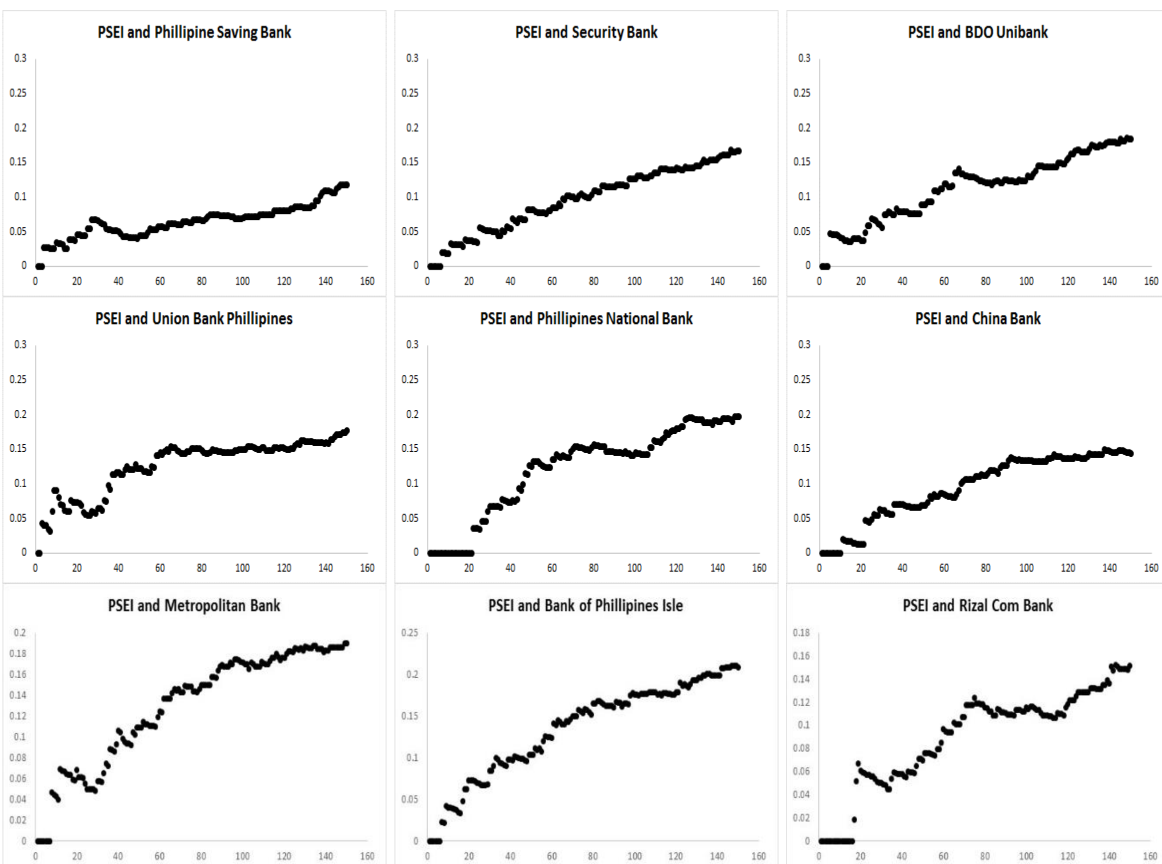


Scatter Plot Philippines Stock Market and Bank Stock Return

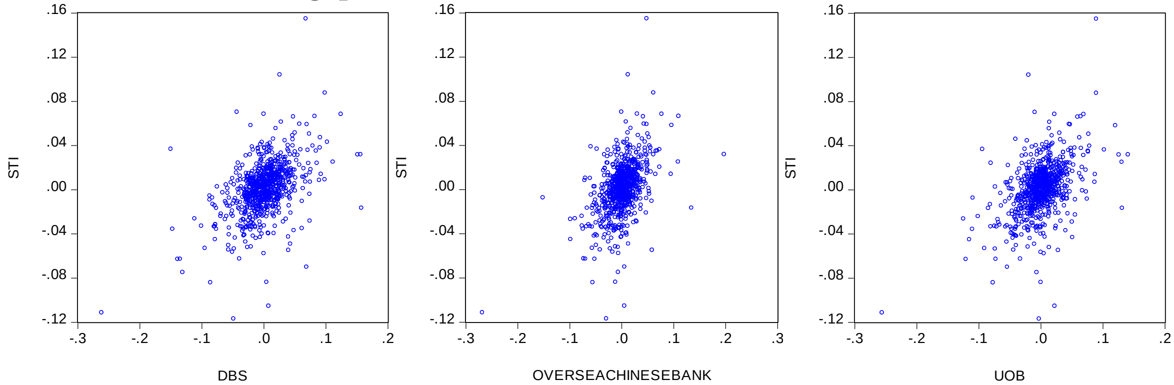




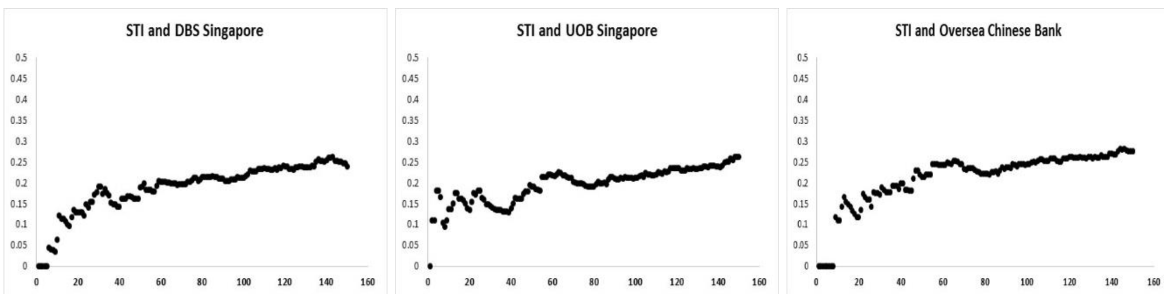
Linkage Estimator Plot: Phillipines PSEI and Phillipines Bank Stock Return



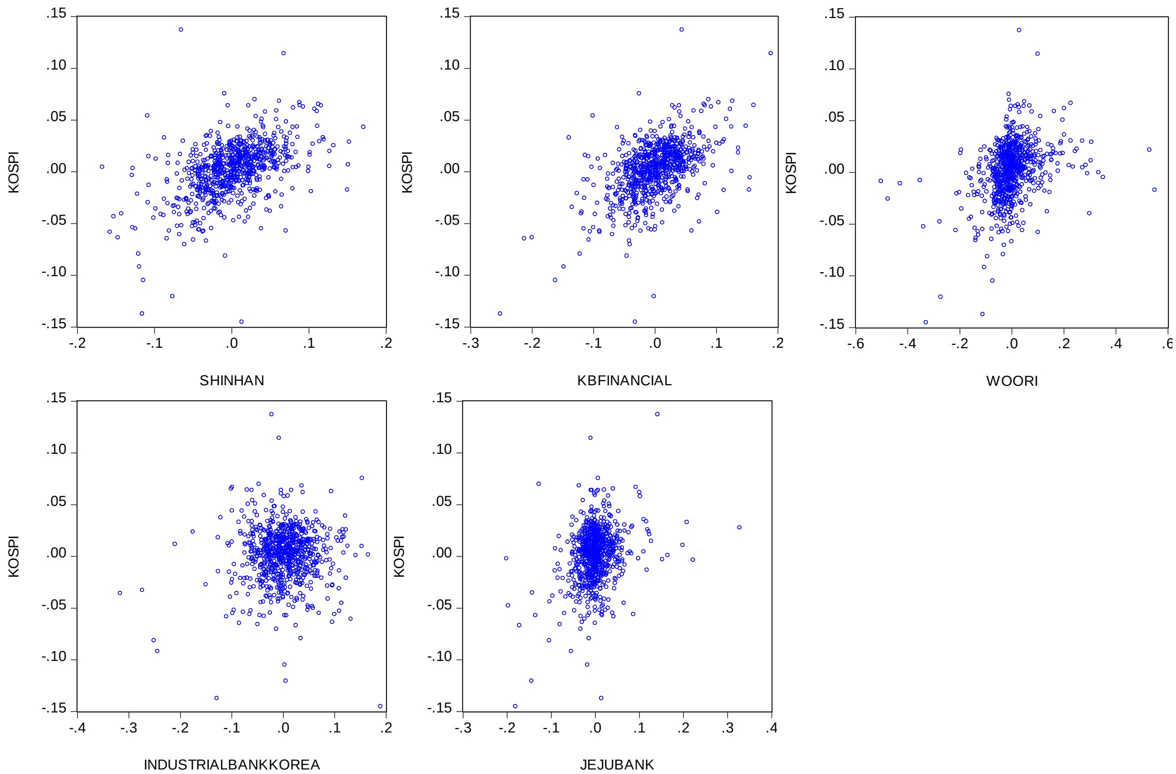
Scatter Plot South Singapore Stock Market and Bank Stock Return



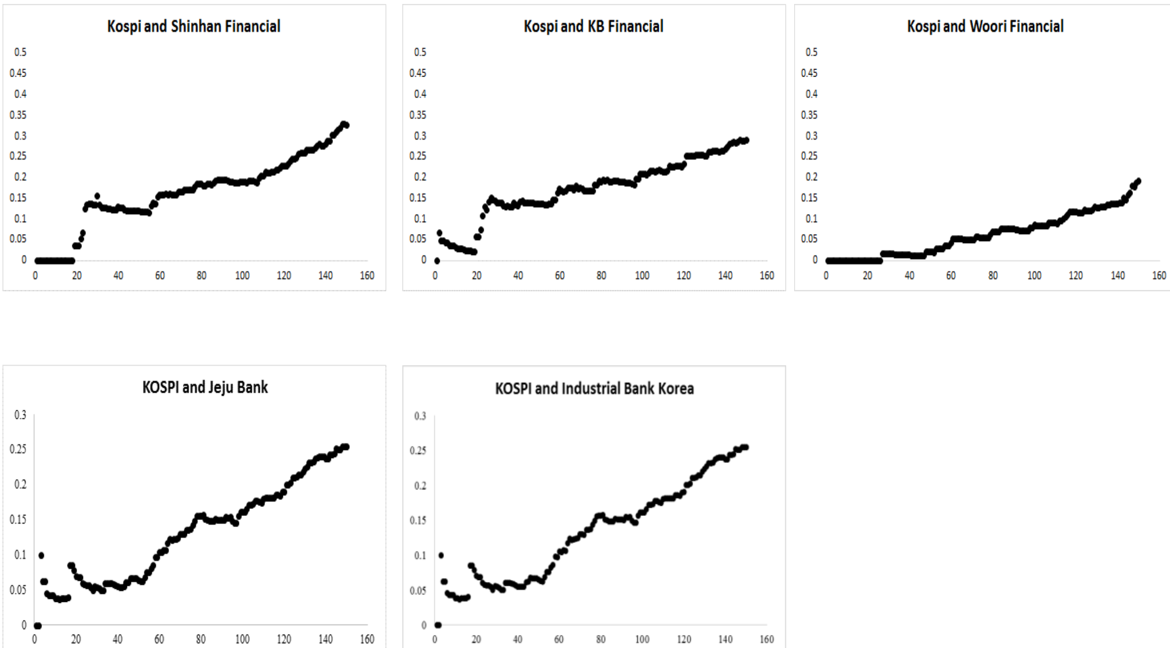
Tail Plot Market Return: STI and Singapore Bank



Scatter Plot South Korea Stock Market and Bank Stock Return



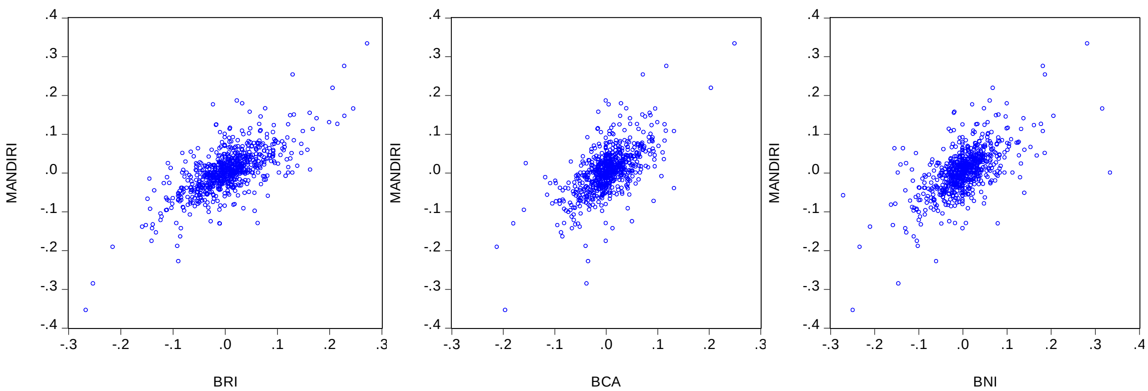
Tail Plot Market Return: KOSPI and South Korea Bank

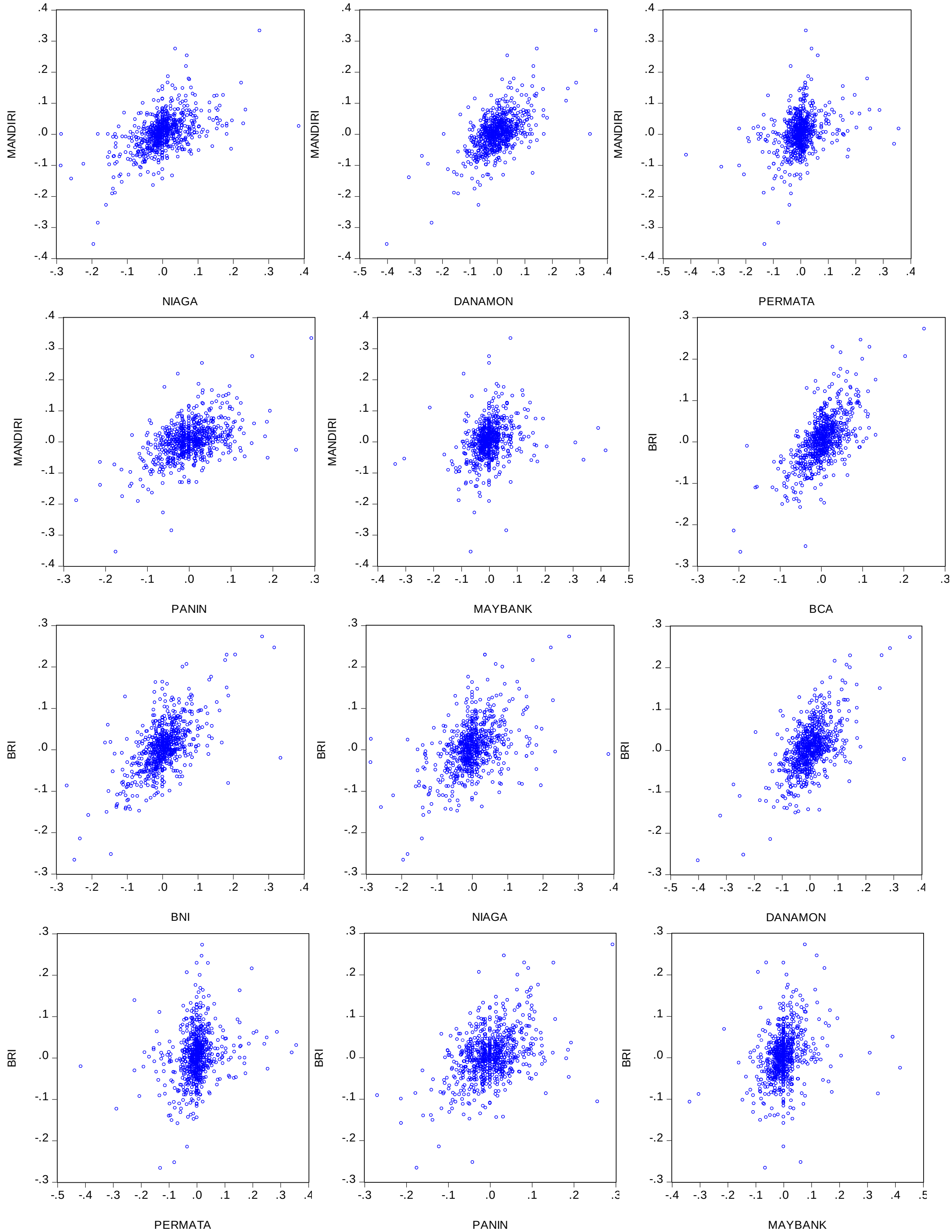


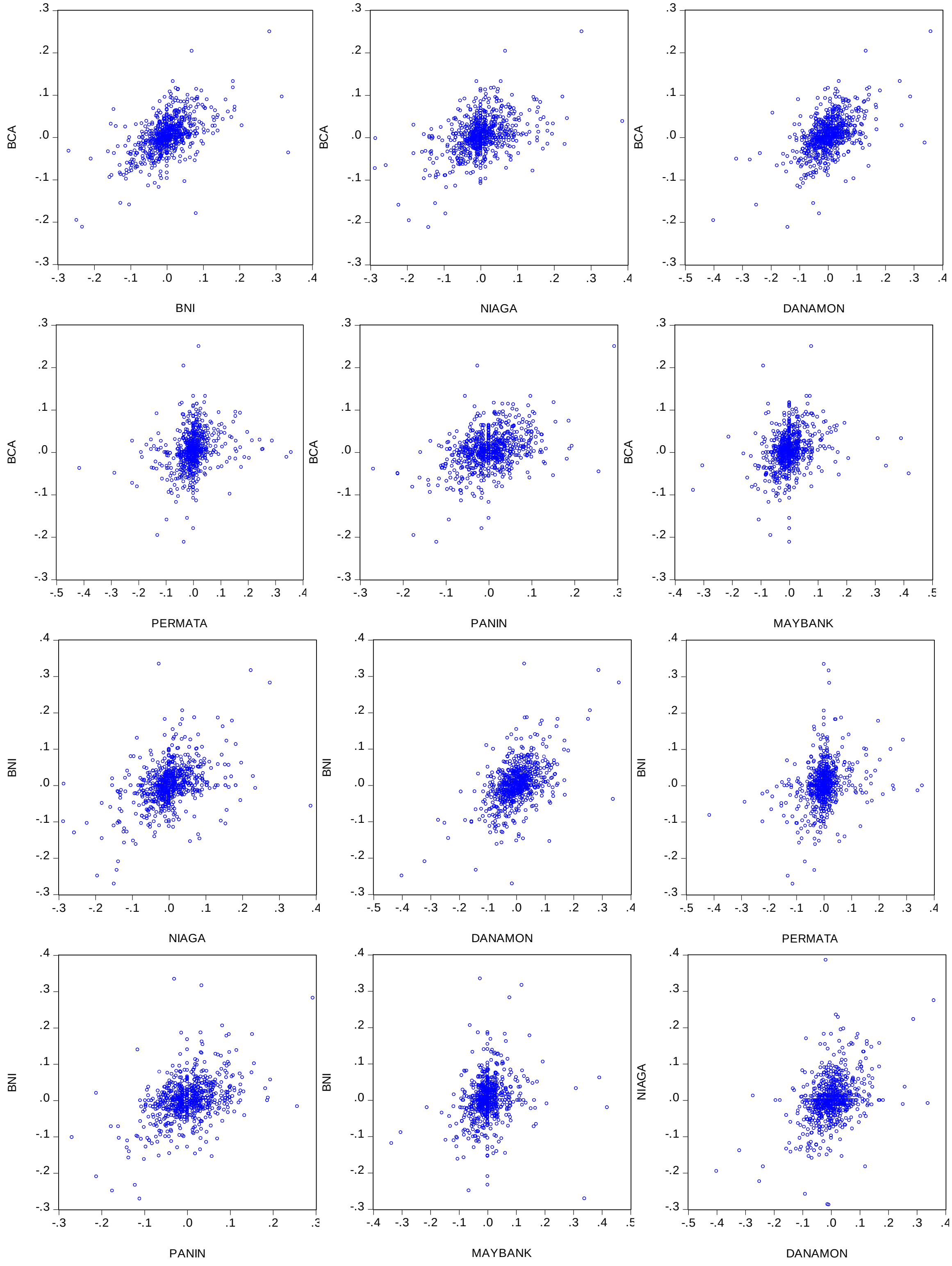
Domestic Bank Stock Returns Scatter Plot

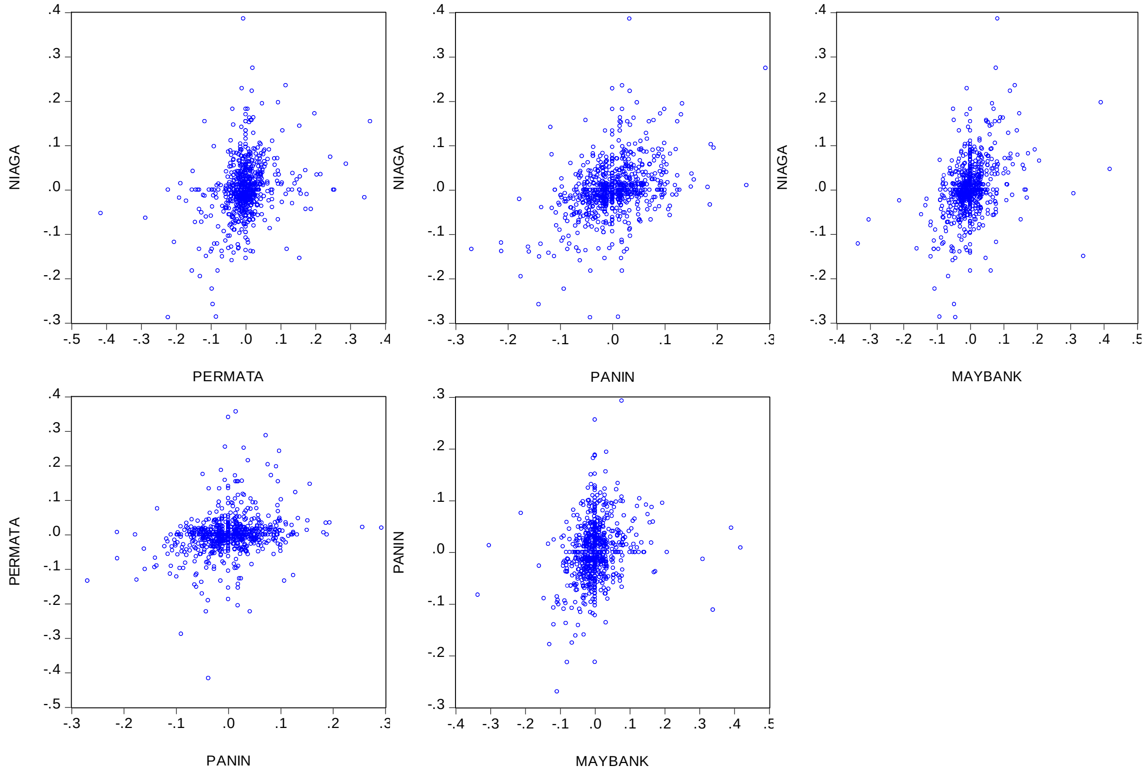
Indonesia

In this part, we provide the scatter plots of some pairs of emerging Asia bank stock returns in the domestic banking system that we use in our analysis. We conclude the asymptotic dependency between pairs of bank stock returns in Table 9 in the Chapter 5 part Results and Discussion.



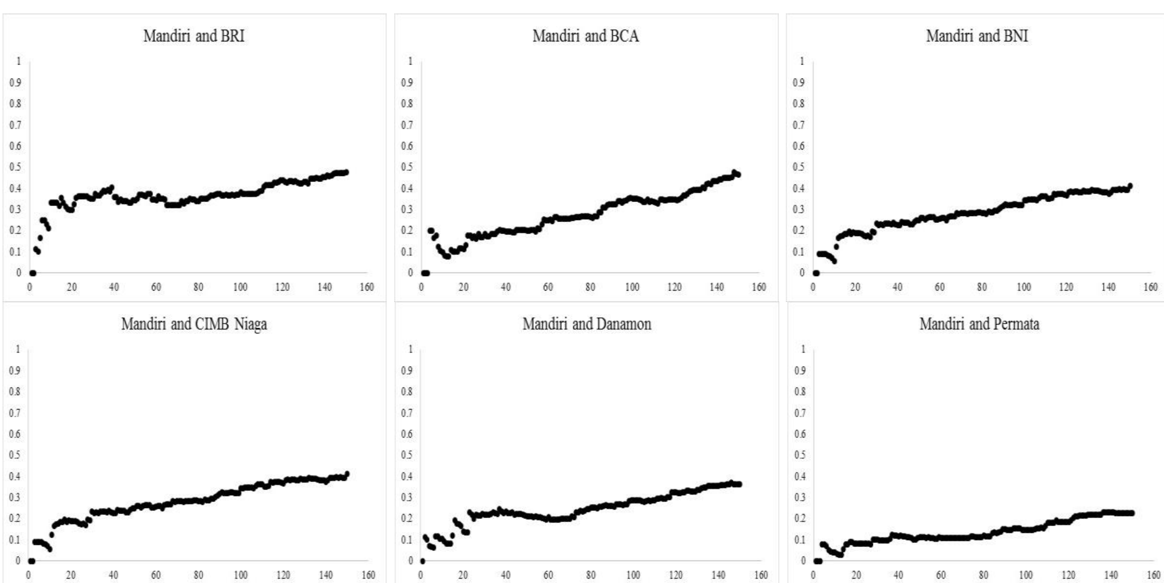

MANDIRI
NIAGA
MANDIRI
DANAMON
MANDIRI
PERMATA
MANDIRI
PANIN
MANDIRI
MAYBANK
BRI
BCA
BRI
BNI
BRI
NIAGA
BRI
DANAMON
BRI
PERMATA
BRI
PANIN
BRI
MAYBANK

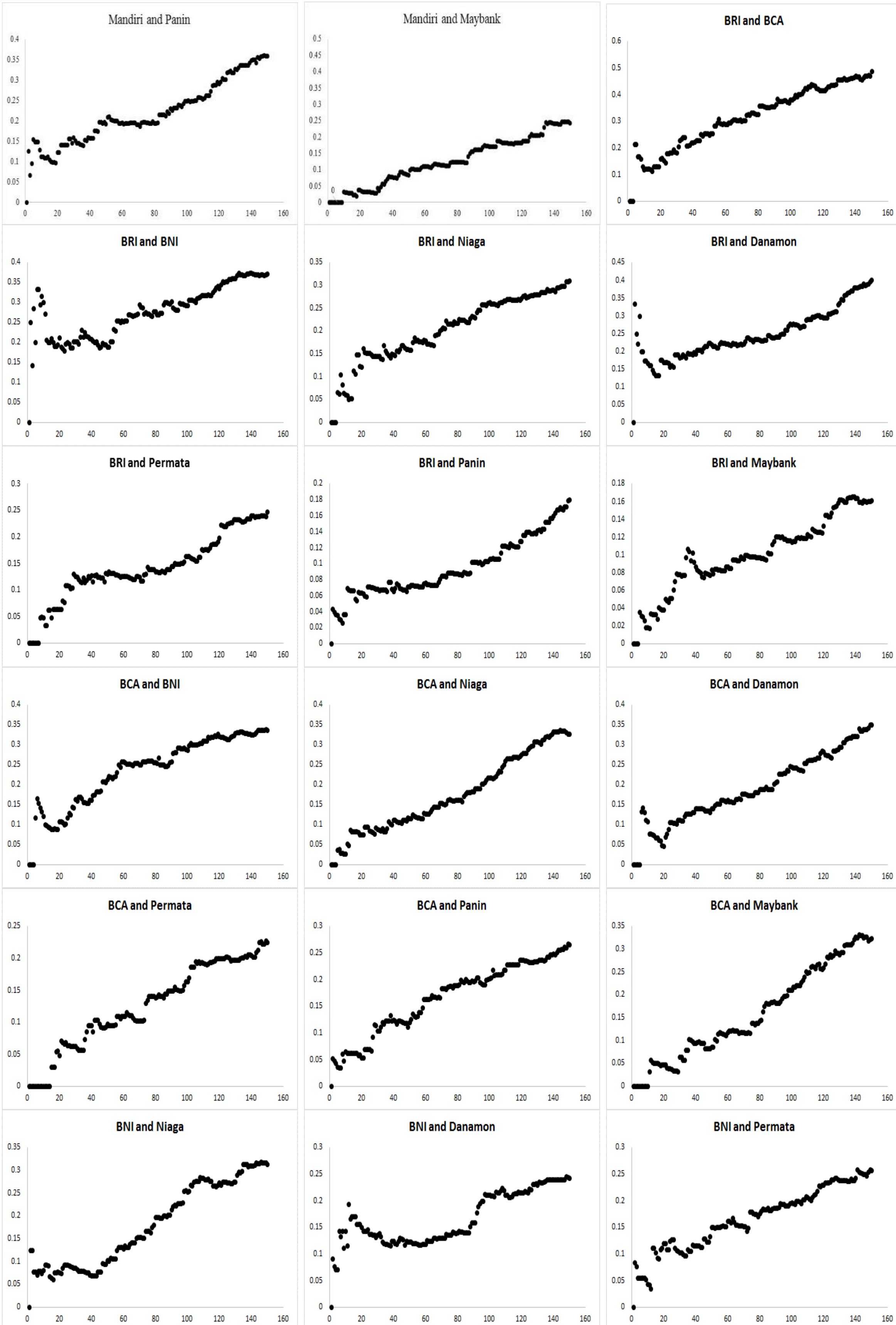

BCA
BNI
BCA
NIAGA
BCA
DANAMON
BCA
PERMATA
BCA
PANIN
BCA
MAYBANK
BNI
NIAGA
BNI
DANAMON
BNI
PERMATA
BNI
PANIN
BNI
MAYBANK
NIAGA
DANAMON

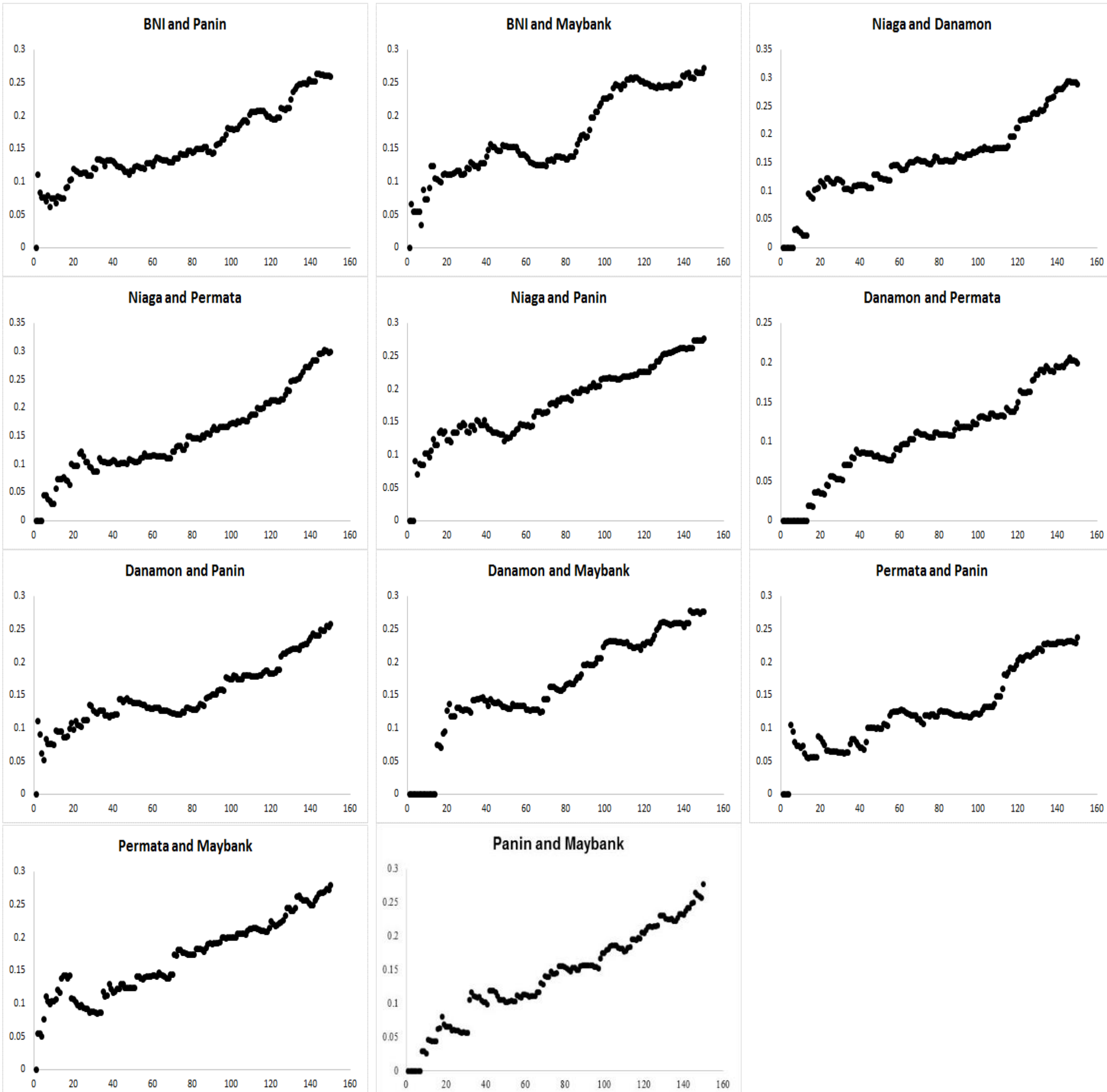


Linkage Estimator Plot: Indonesian Bank Stock Return

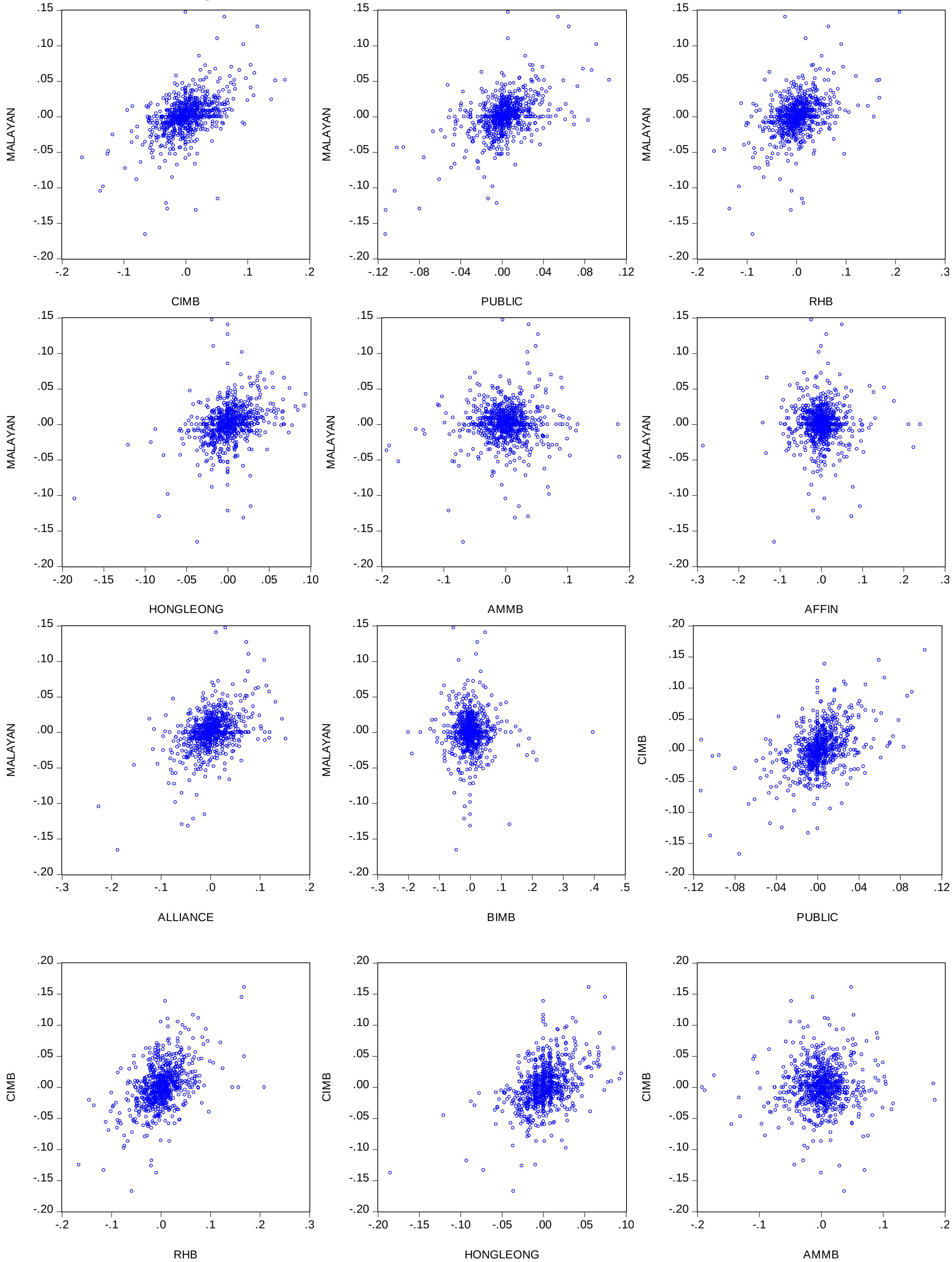
In this part, we provide the linkages estimator plots of emerging Asia bank stock returns in the domestic banking system that we use in our analysis. We conclude the probability of extreme event *E{k|k≥1}* in Table 9 in the Chapter 5 part Results and Discussion. The y-axis gives the descending ordered statistics of the tail dependence estimator $E\{k|k \geq 1\}-1$, while the x-axis gives the rank order of thresholds.

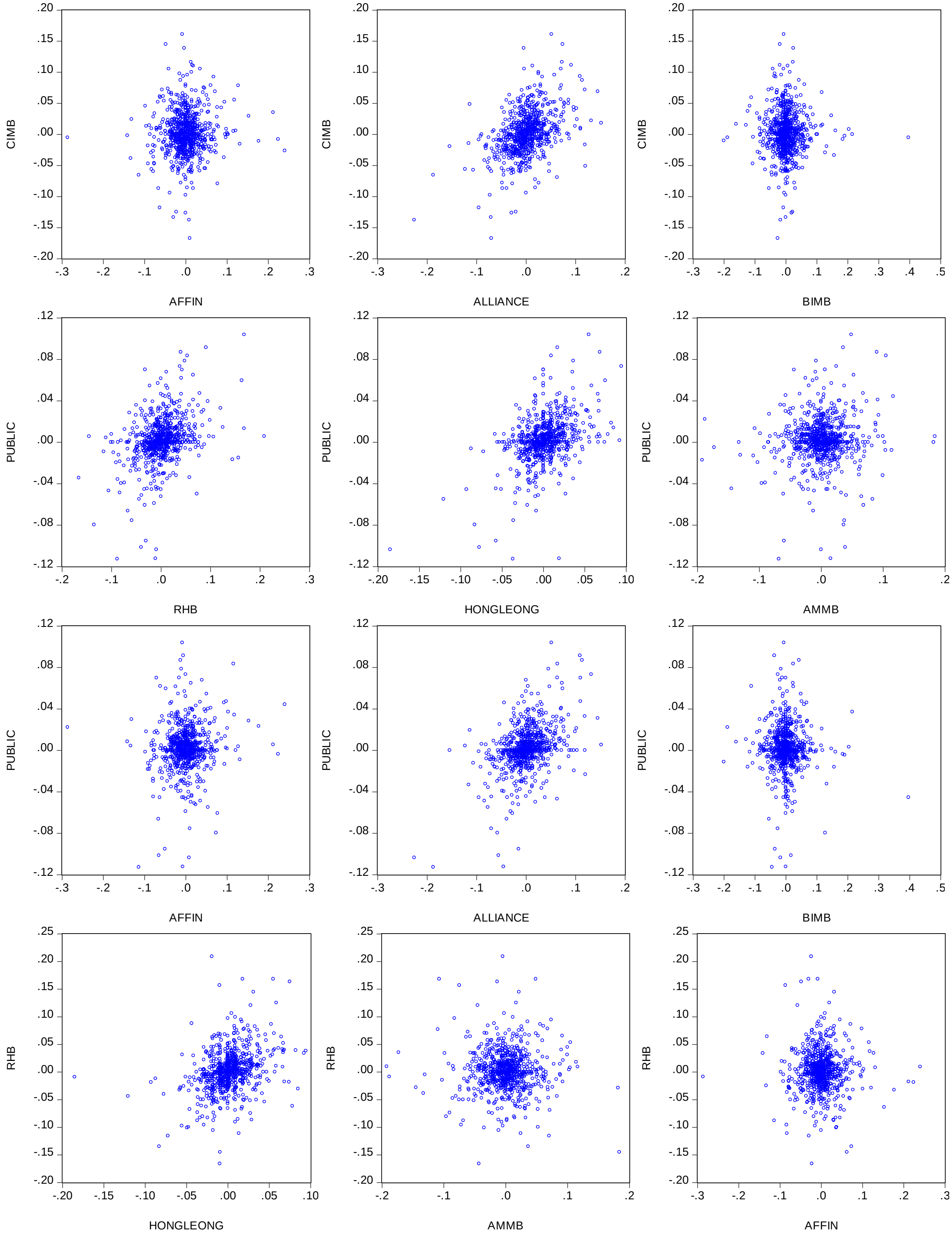


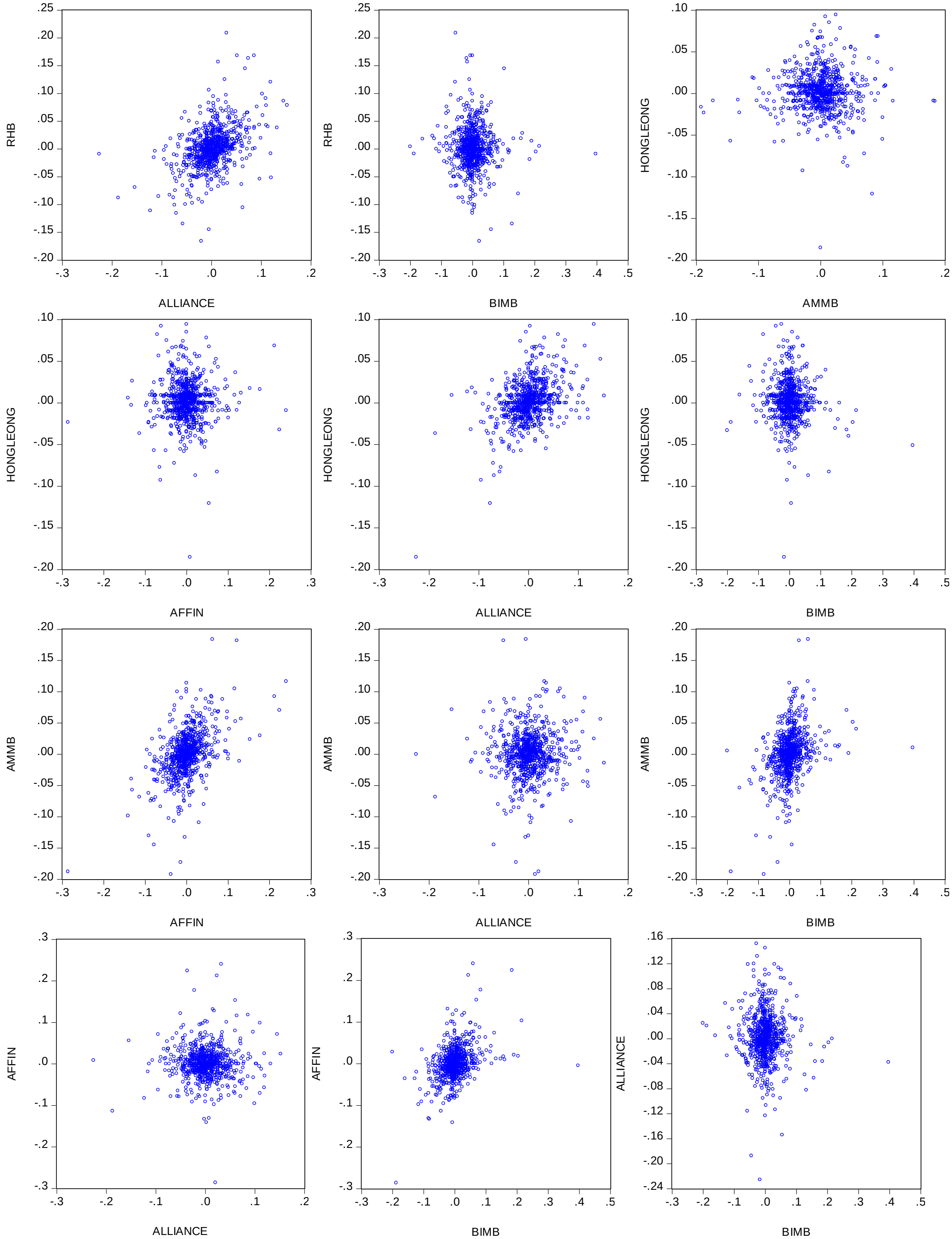

Mandiri and Panin
Mandiri and Maybank
BRI and BCA
BRI and BNI
BRI and Niaga
BRI and Danamon
BRI and Permata
BRI and Panin
BRI and Maybank
BCA and BNI
BCA and Niaga
BCA and Danamon
BCA and Permata
BCA and Panin
BCA and Maybank
BNI and Niaga
BNI and Danamon
BNI and Permata


BNI and Panin
BNI and Maybank
Niaga and Danamon
Niaga and Permata
Niaga and Panin
Danamon and Permata
Danamon and Panin
Danamon and Maybank
Permata and Panin
Permata and Maybank
Panin and Maybank

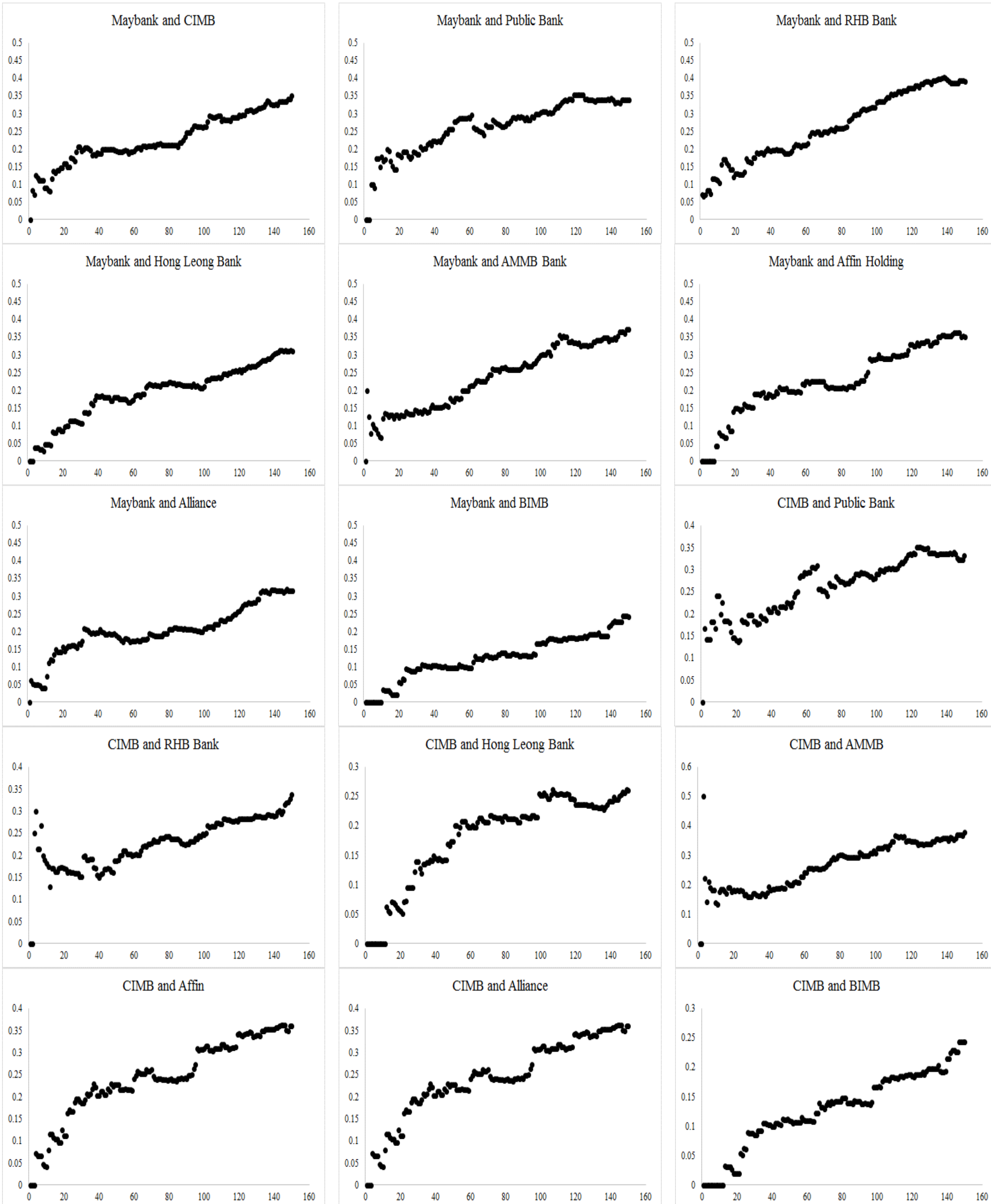
Scatter Plot: Malaysian Bank Returns

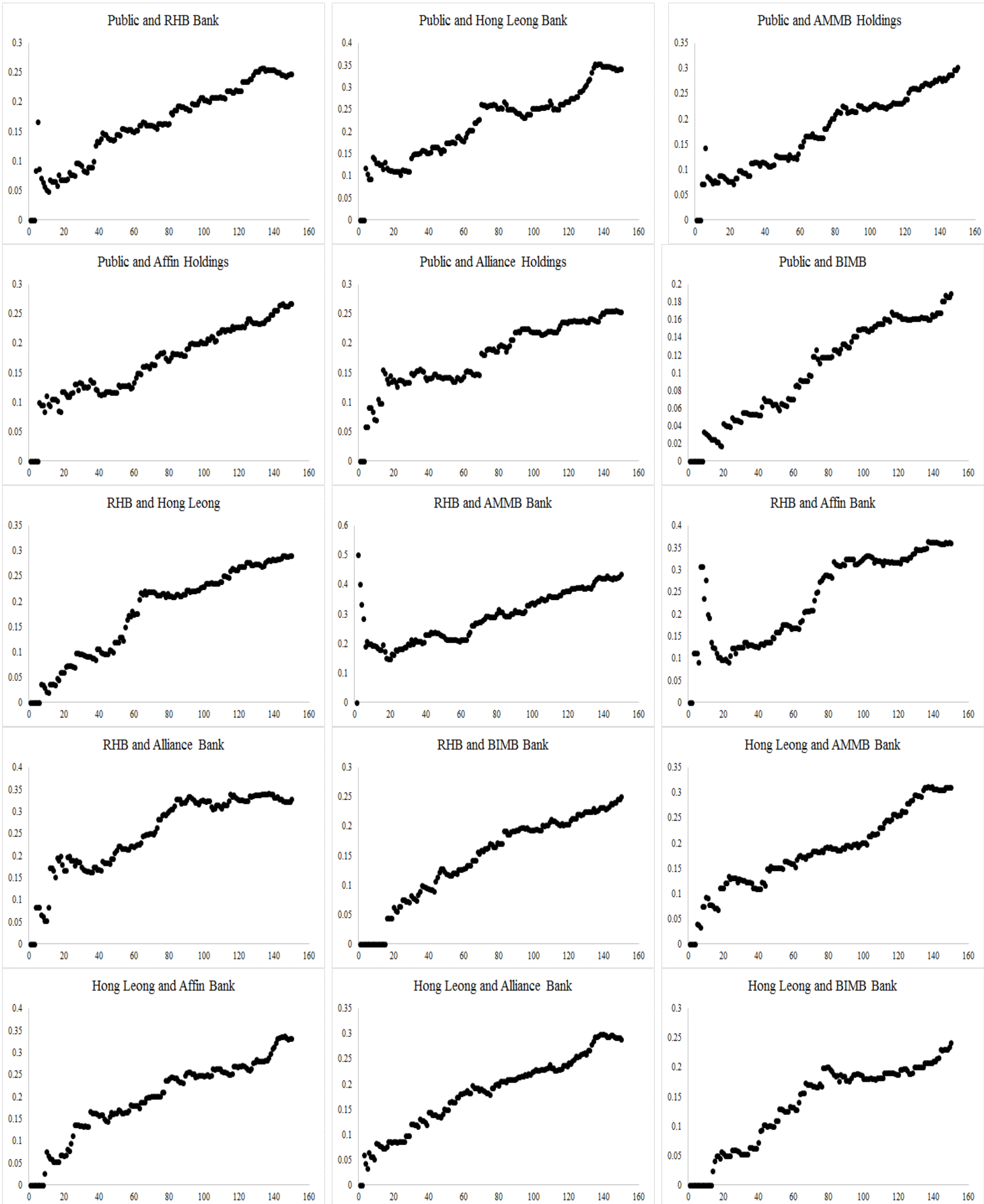



CIMB
AFFIN
CIMB
ALLIANCE
CIMB
BIMB
PUBLIC
RHB
PUBLIC
HONGLEONG
PUBLIC
AMMB
PUBLIC
AFFIN
PUBLIC
ALLIANCE
PUBLIC
BIMB
RHB
HONGLEONG
RHB
AMMB
RHB
AFFIN

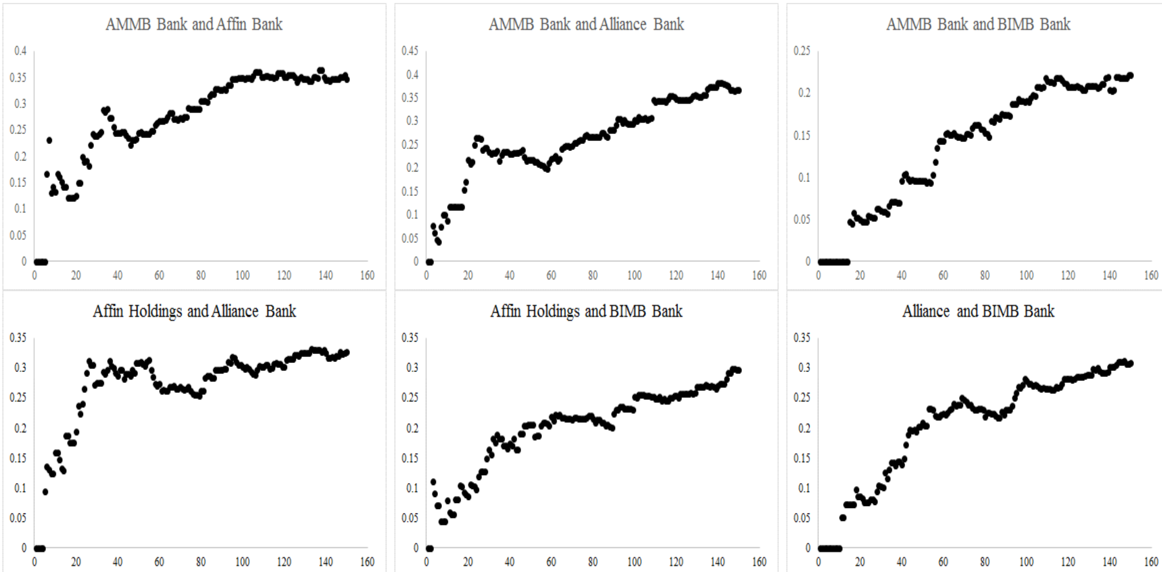

RHB
.25
.20
.15
.10
.05
.00
-.05
-.10
-.15
-.20
-.3 -.2 -.1 .0 .1 .2
ALLIANCE
RHB
-.3 -.2 -.1 .0 .1 .2 .3 .4 .5
BIMB
HONGLEONG
-.2 -.1 .0 .1 .2
AMMB
HONGLEONG
-.3 -.2 -.1 .0 .1 .2 .3
AFFIN
HONGLEONG
-.3 -.2 -.1 .0 .1 .2
ALLIANCE
HONGLEONG
-.3 -.2 -.1 .0 .1 .2 .3 .4 .5
BIMB
AMMB
-.3 -.2 -.1 .0 .1 .2 .3
AFFIN
AMMB
-.3 -.2 -.1 .0 .1 .2
ALLIANCE
AMMB
-.3 -.2 -.1 .0 .1 .2 .3 .4 .5
BIMB
AFFIN
.3
.2
.1
.0
-.1
-.2
-.3
-.3 -.2 -.1 .0 .1 .2
ALLIANCE
AFFIN
-.3 -.2 -.1 .0 .1 .2 .3 .4 .5
BIMB
ALLIANCE
.16
.12
.08
.04
.00
-.04
-.08
-.12
-.16
-.20
-.24
-.3 -.2 -.1 .0 .1 .2 .3 .4 .5
BIMB

Linkage Estimator Plot: Malaysian Bank Stock Returns

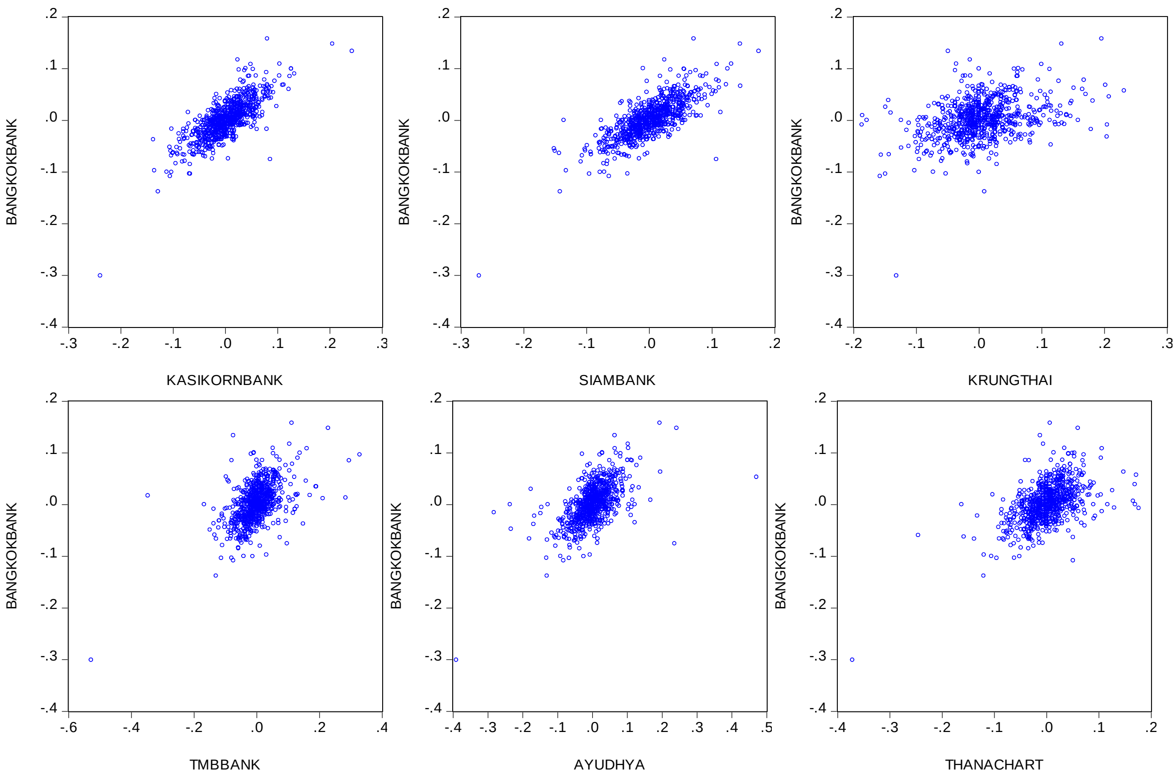


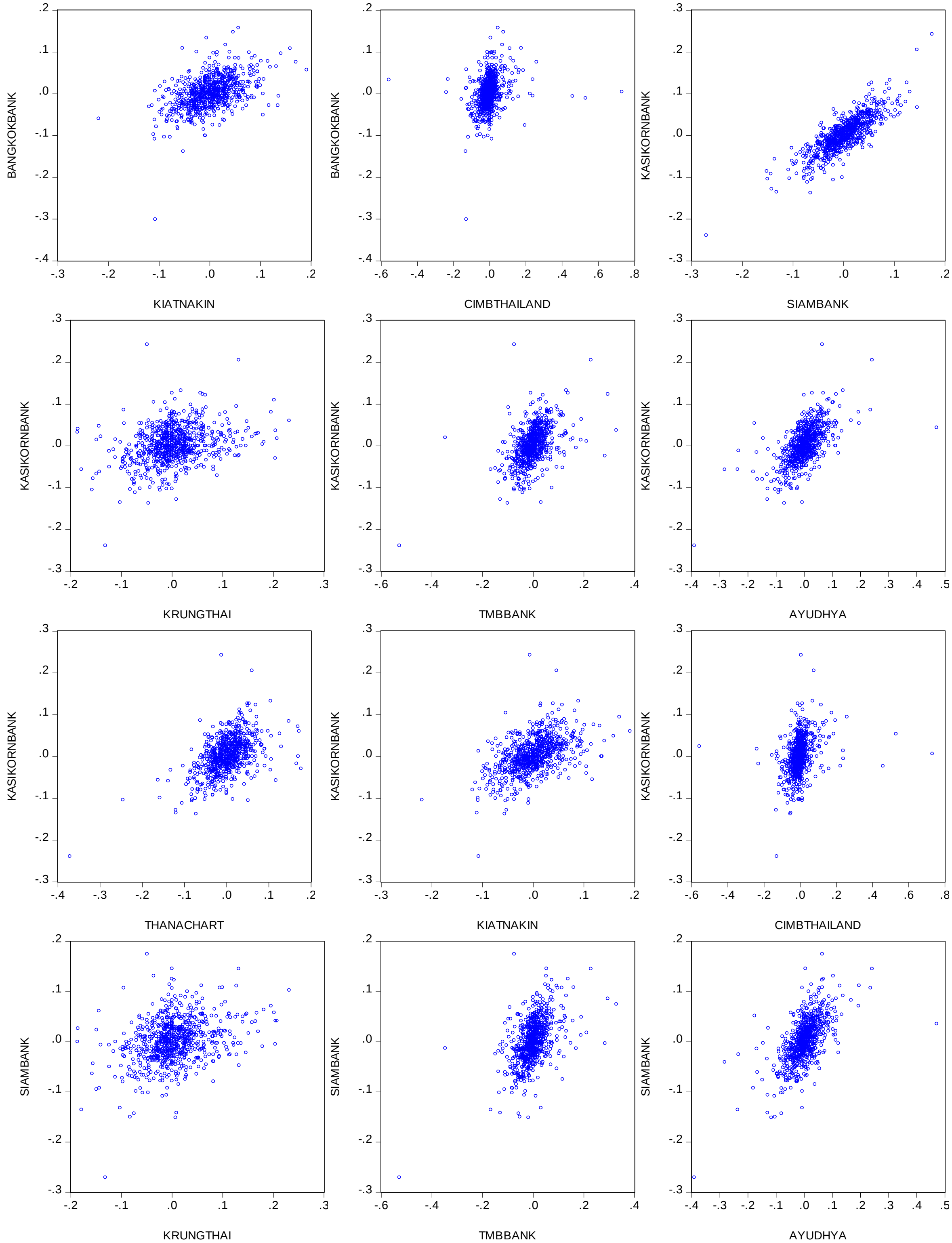


Public and RHB Bank
Public and Hong Leong Bank
Public and AMMB Holdings
Public and Affin Holdings
Public and Alliance Holdings
Public and BIMB
RHB and Hong Leong
RHB and AMMB Bank
RHB and Affin Bank
RHB and Alliance Bank
RHB and BIMB Bank
Hong Leong and AMMB Bank
Hong Leong and Affin Bank
Hong Leong and Alliance Bank
Hong Leong and BIMB Bank



Scatter Plot: Thailand Bank Stock Returns




BANGKOKBANK
KIATNAKIN
BANGKOKBANK
CIMBTHAILAND
KASIKORNBANK
SIAMBANK
KASIKORNBANK
KRUNGTHAI
KASIKORNBANK
TMBBANK
KASIKORNBANK
AYUDHYA
KASIKORNBANK
THANACHART
KASIKORNBANK
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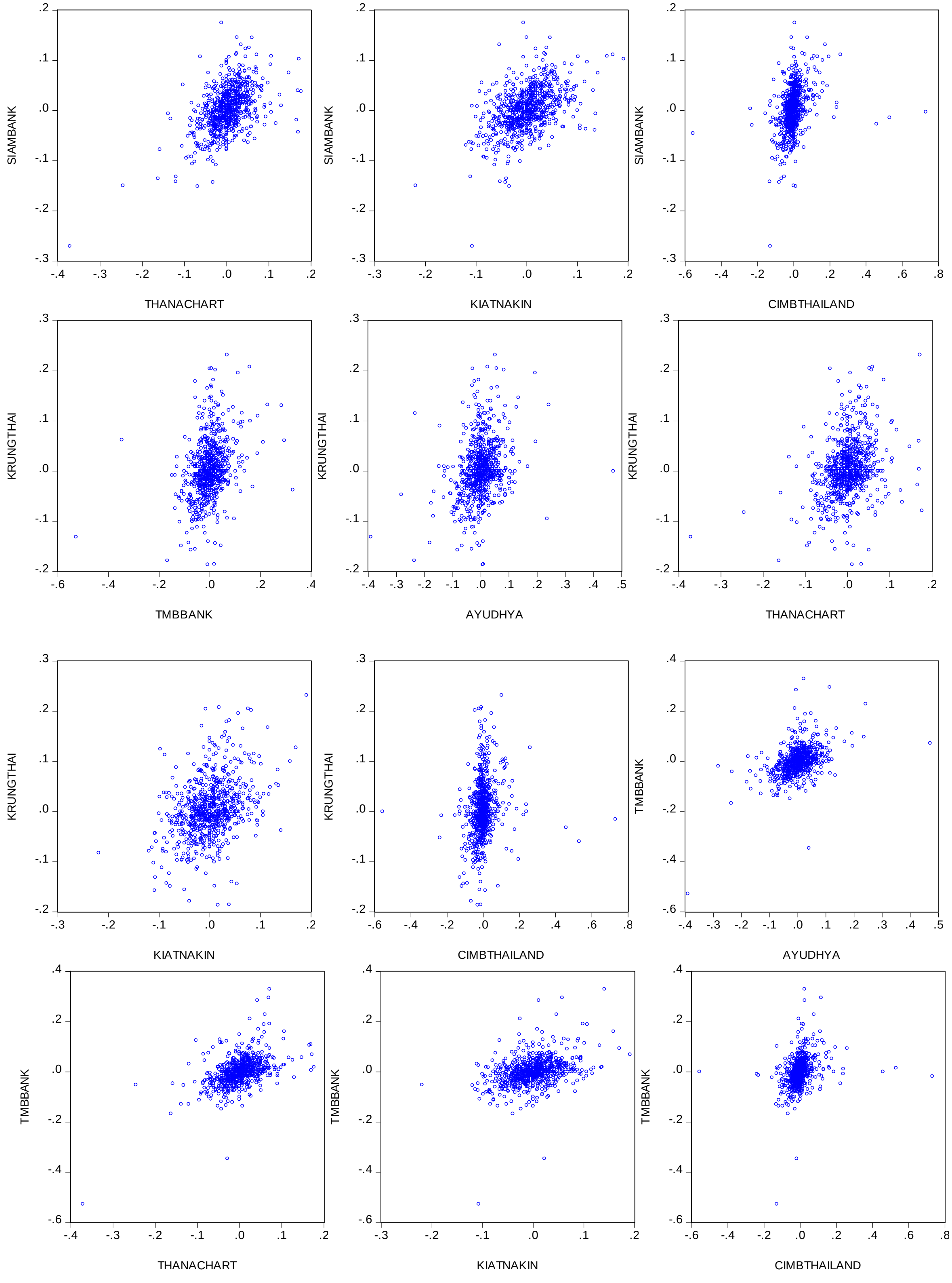
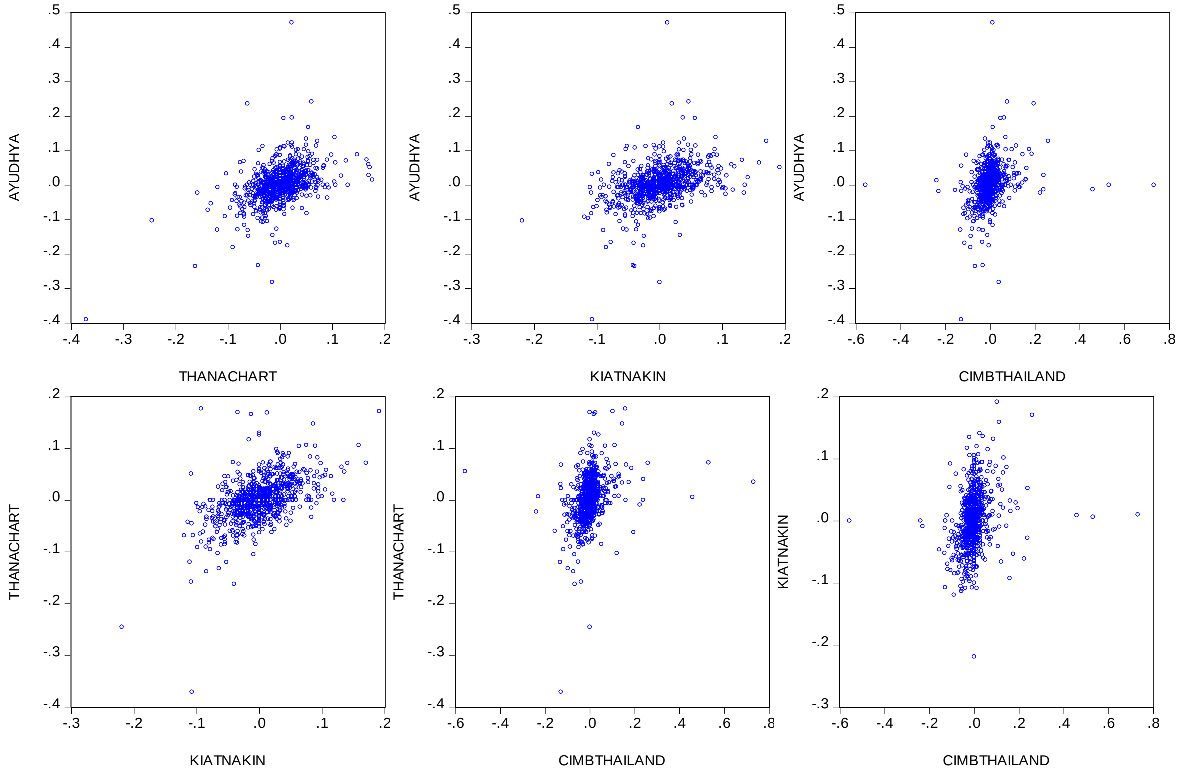
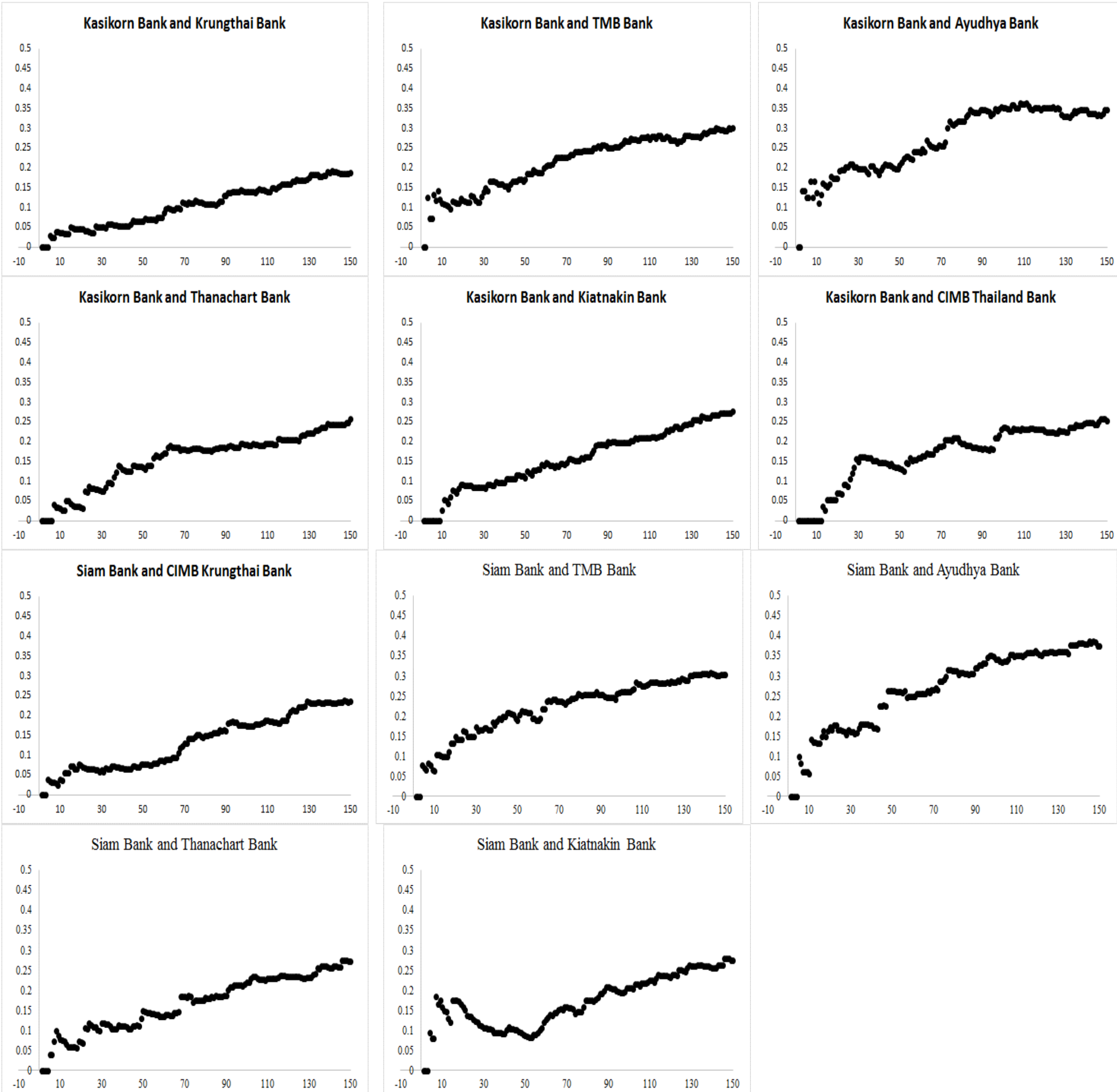
SIAMBANK
AYUDHYA

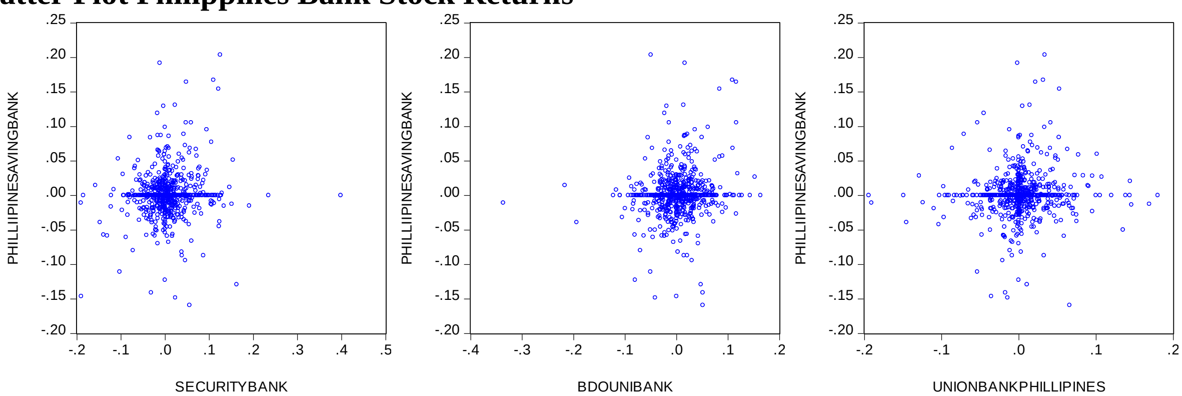

SIAMBANK
THANACHART
SIAMBANK
KIATNAKIN
SIAMBANK
CIMBTHAILAND
KRUNGTHAI
TMBBANK
KRUNGTHAI
AYUDHYA
KRUNGTHAI
THANACHART
KRUNGTHAI
KIATNAKIN
KRUNGTHAI
CIMBTHAILAND
TMBBANK
AYUDHYA
TMBBANK
THANACHART
TMBBANK
KIATNAKIN
TMBBANK
CIMBTHAILAND

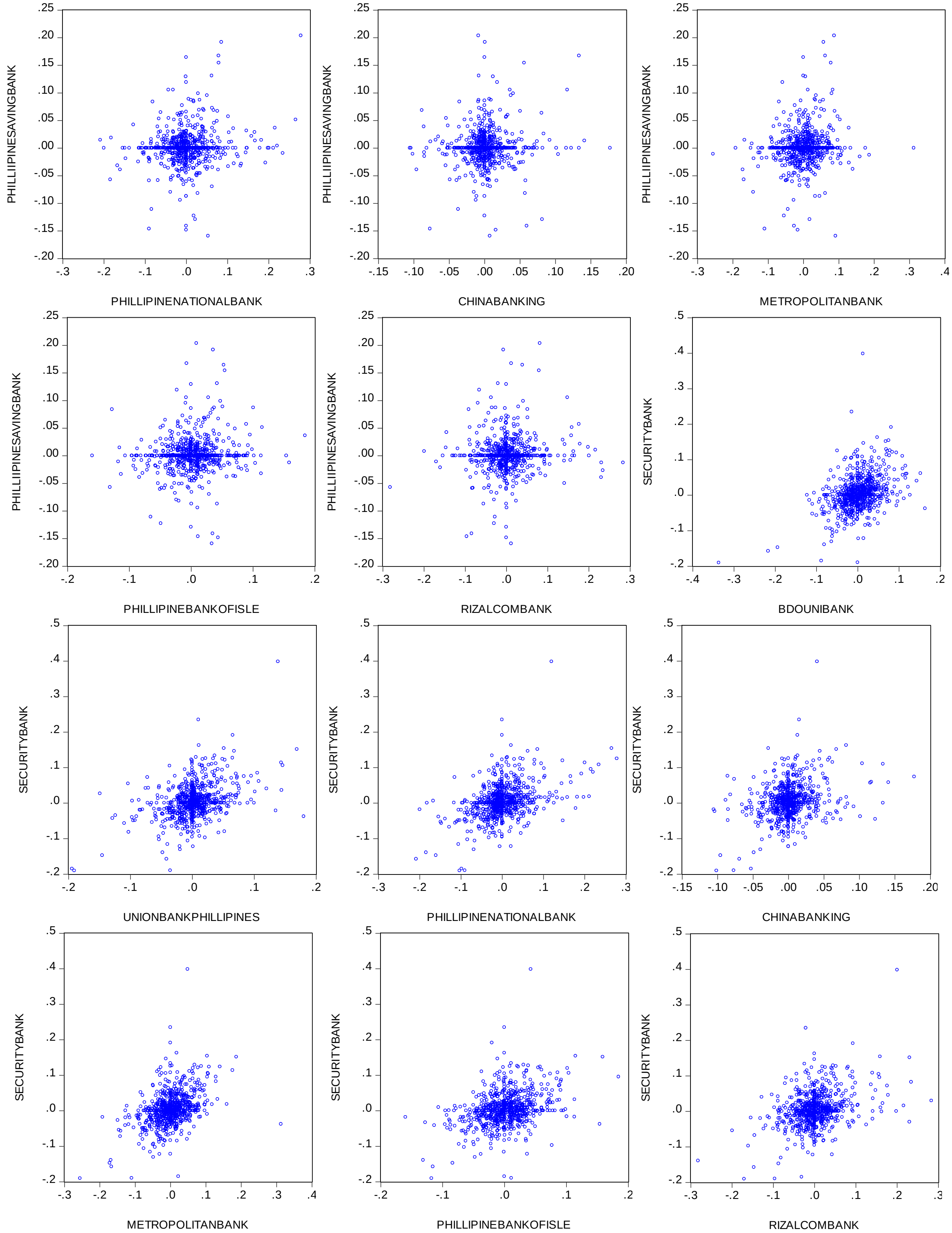


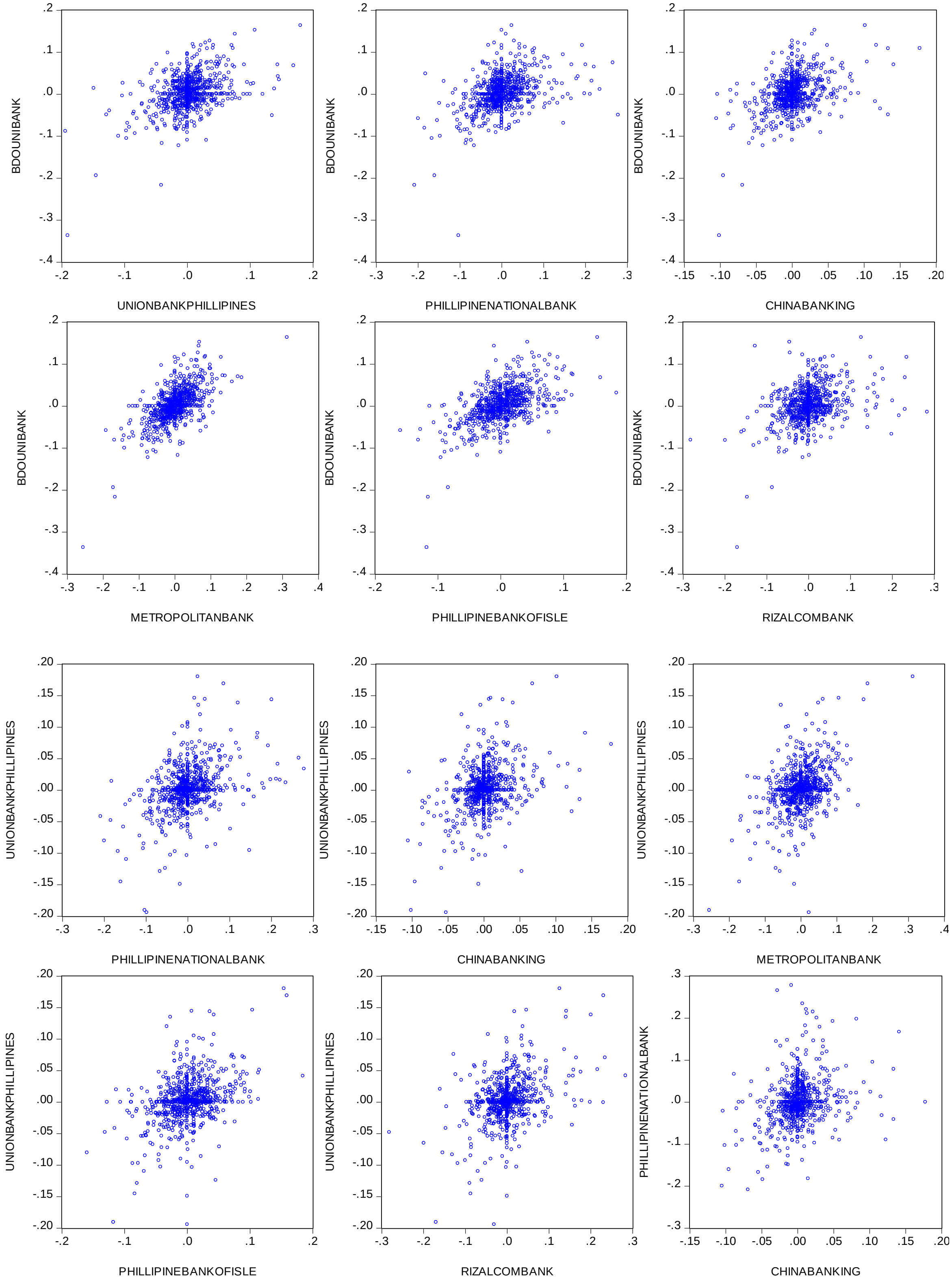
Linkage Estimator Plot: Thailand Bank Stock Returns

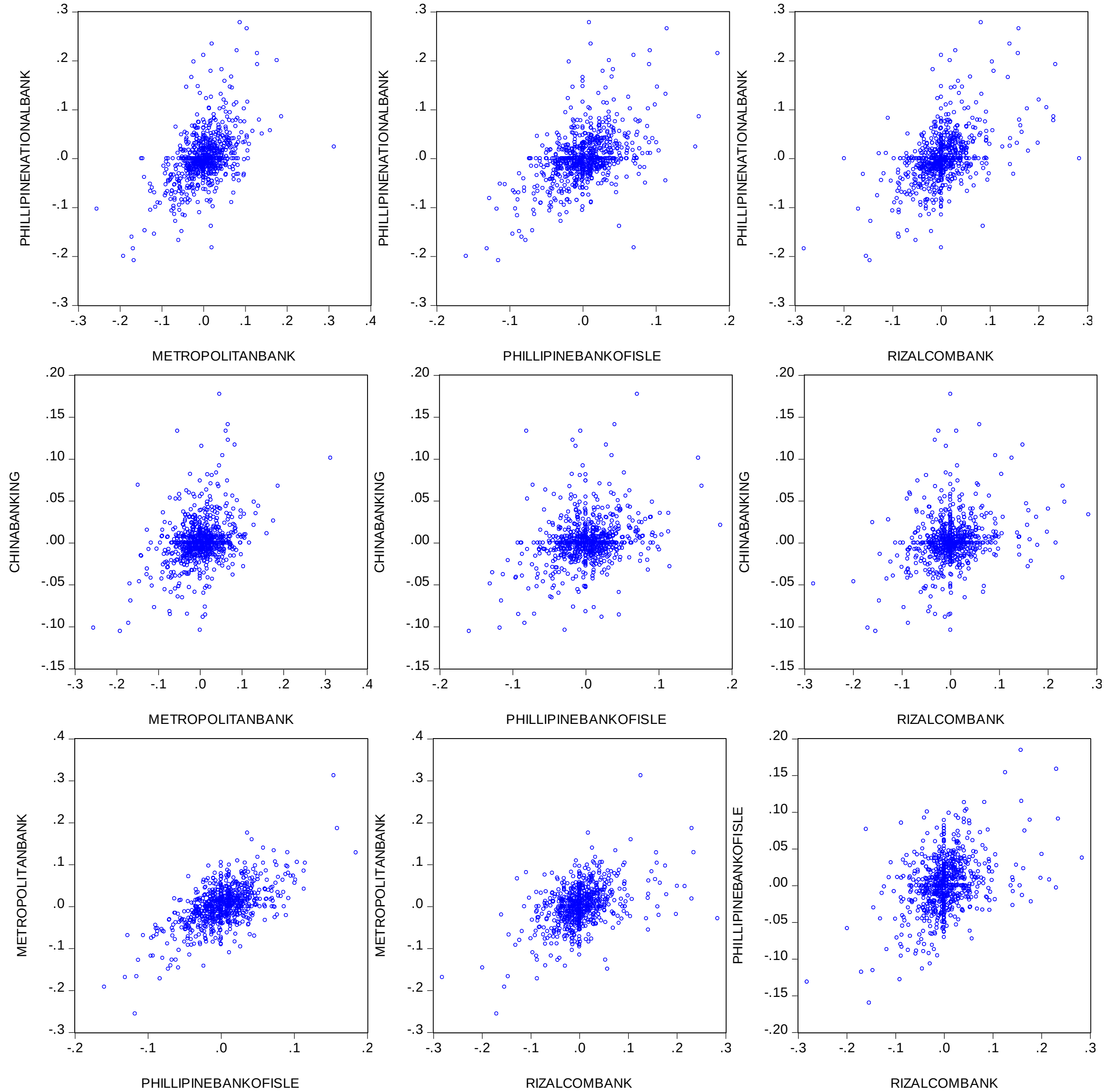


Scatter Plot Philippines Bank Stock Returns

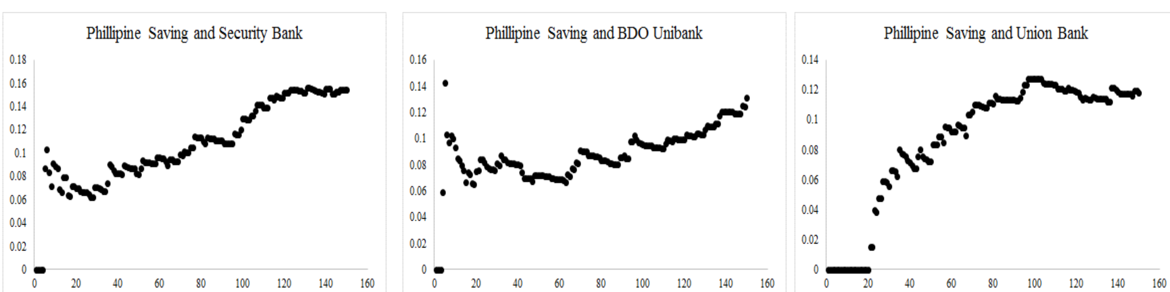


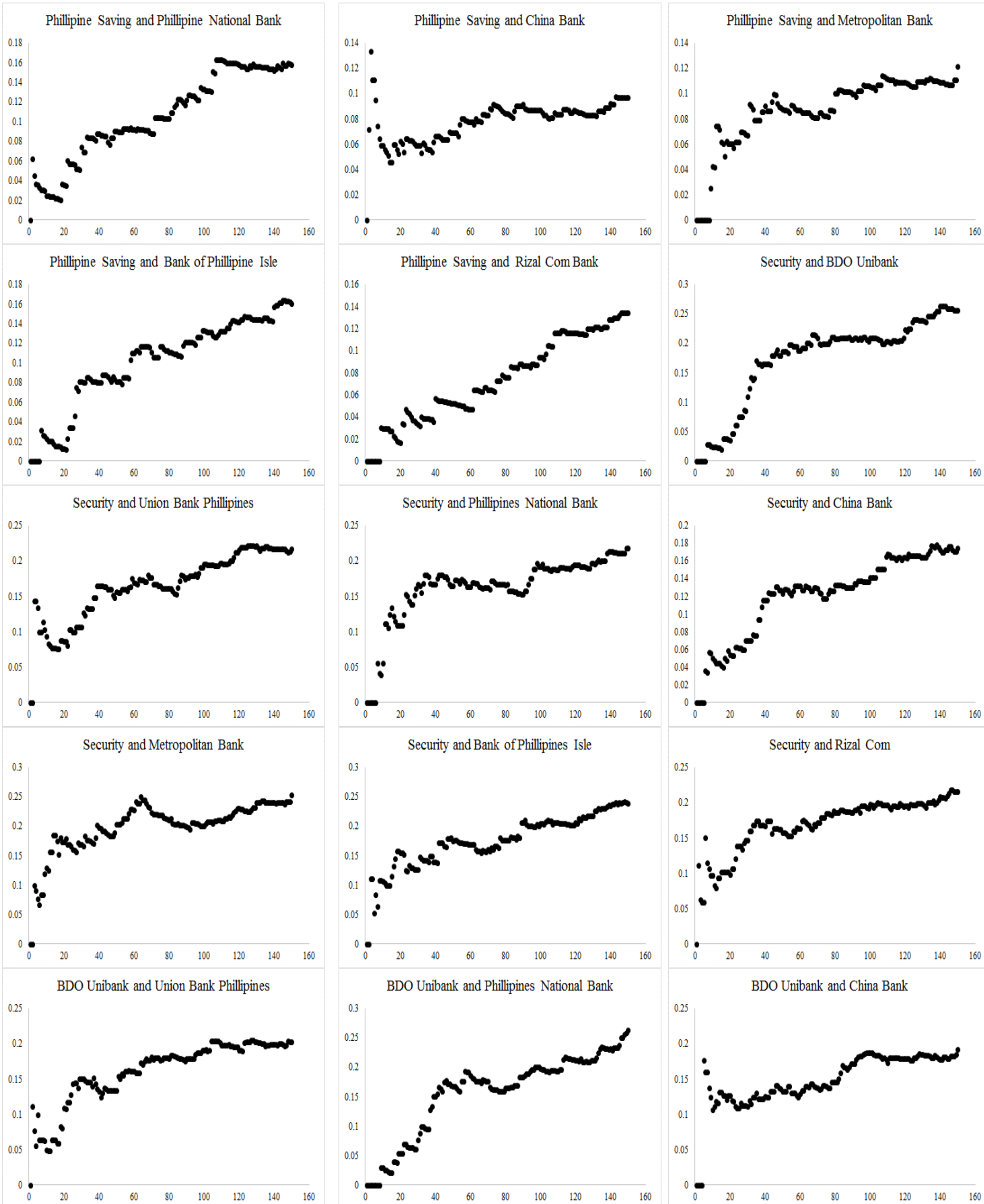

PHILLIIPINESAVINGBANK
PHILLIPINENATIONALBANK
PHILLIIPINESAVINGBANK
CHINABANKING
PHILLIIPINESAVINGBANK
METROPOLITANBANK
PHILLIIPINESAVINGBANK
PHILLIPINEBANKOFISLE
PHILLIIPINESAVINGBANK
RIZALCOMBANK
SECURITYBANK
BDOUNIBANK
SECURITYBANK
UNIONBANKPHILLIPINES
SECURITYBANK
PHILLIPINENATIONALBANK
SECURITYBANK
CHINABANKING
SECURITYBANK
METROPOLITANBANK
SECURITYBANK
PHILLIPINEBANKOFISLE
SECURITYBANK
RIZALCOMBANK

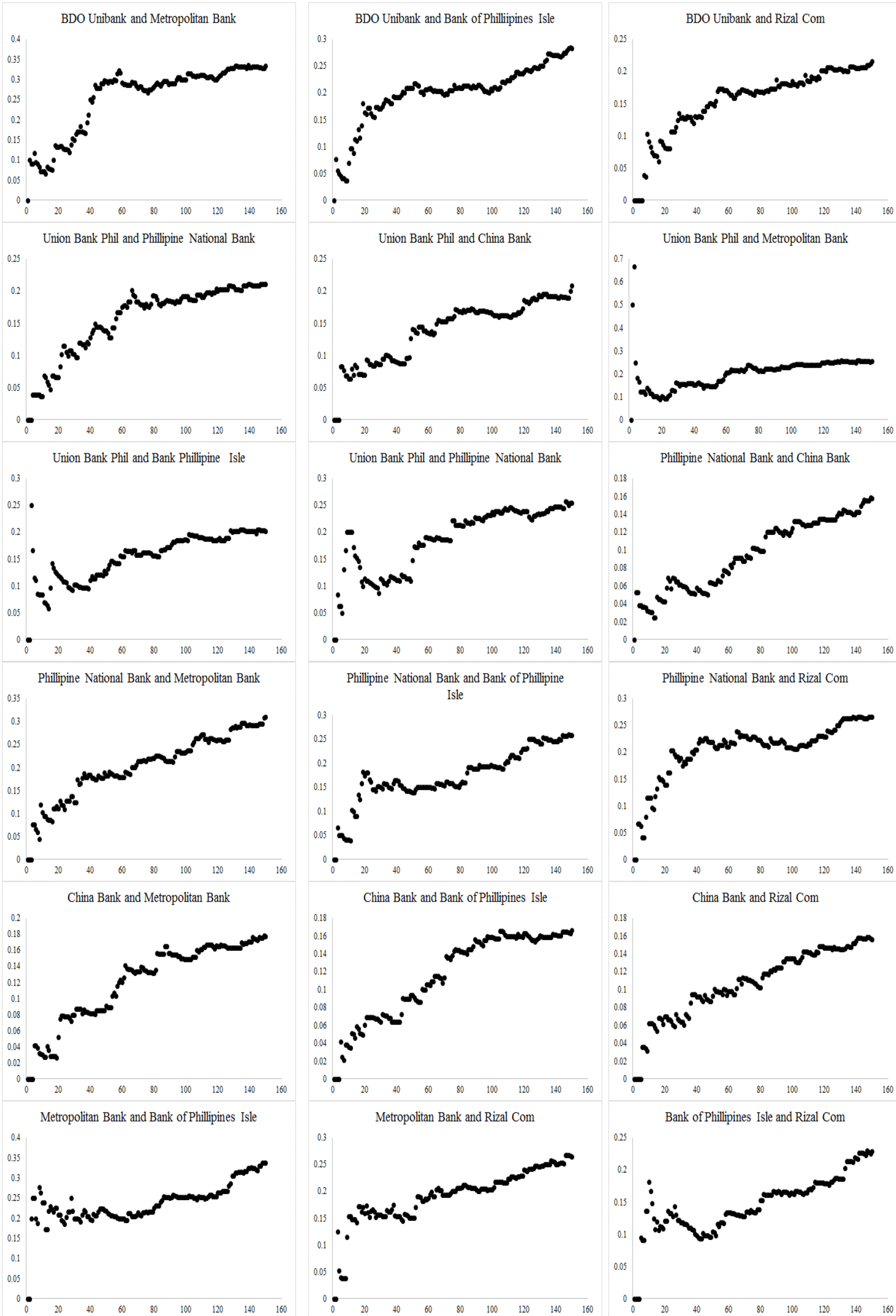

BDOUNIBANK
UNIONBANKPHILLIPINES
BDOUNIBANK
PHILLIPINENATIONALBANK
BDOUNIBANK
CHINABANKING
BDOUNIBANK
METROPOLITANBANK
BDOUNIBANK
PHILLIPINEBANKOFISLE
BDOUNIBANK
RIZALCOMBANK
UNIONBANKPHILLIPINES
PHILLIPINENATIONALBANK
UNIONBANKPHILLIPINES
CHINABANKING
UNIONBANKPHILLIPINES
METROPOLITANBANK
UNIONBANKPHILLIPINES
PHILLIPINEBANKOFISLE
UNIONBANKPHILLIPINES
RIZALCOMBANK
PHILLIPINENATIONALBANK
CHINABANKING



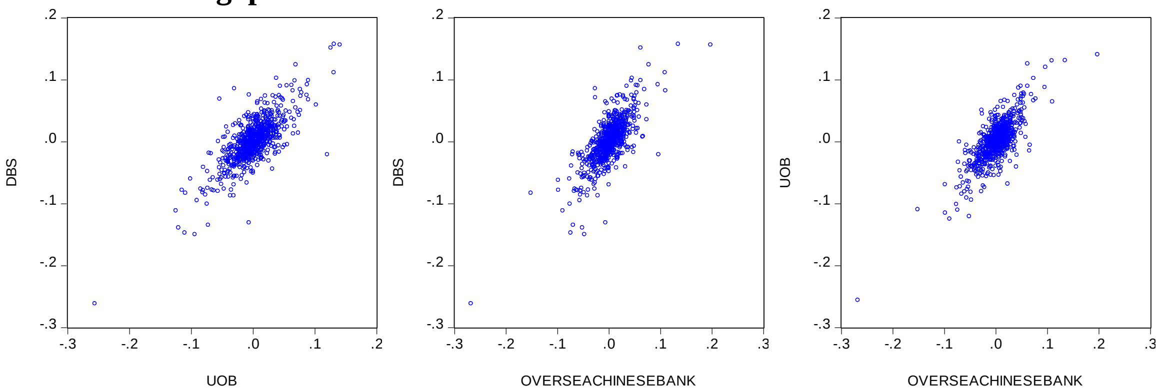
Linkage Estimator Plot: Philippines Bank Stock Returns



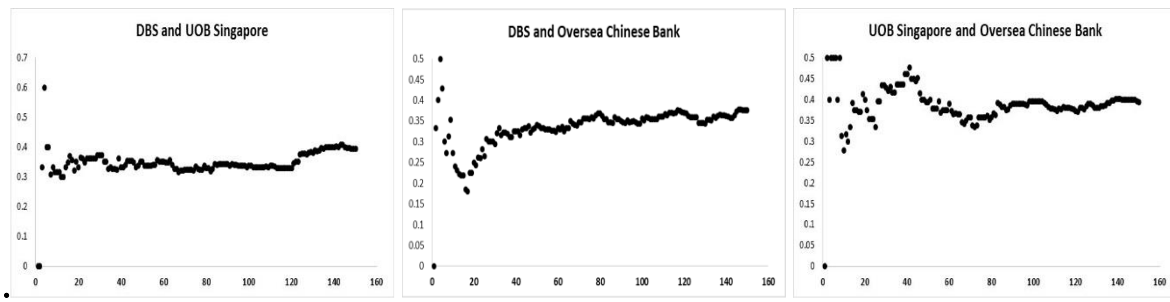

Phillipine Saving and Phillipine National Bank
Phillipine Saving and China Bank
Phillipine Saving and Metropolitan Bank
Phillipine Saving and Bank of Phillipine Isle
Phillipine Saving and Rizal Com Bank
Security and BDO Unibank
Security and Union Bank Phillipines
Security and Phillipines National Bank
Security and China Bank
Security and Metropolitan Bank
Security and Bank of Phillipines Isle
Security and Rizal Com
BDO Unibank and Union Bank Phillipines
BDO Unibank and Phillipines National Bank
BDO Unibank and China Bank


BDO Unibank and Metropolitan Bank
BDO Unibank and Bank of Philliipines Isle
BDO Unibank and Rizal Com
Union Bank Phil and Phillipine National Bank
Union Bank Phil and China Bank
Union Bank Phil and Metropolitan Bank
Union Bank Phil and Bank Phillipine Isle
Union Bank Phil and Phillipine National Bank
Phillipine National Bank and China Bank
Phillipine National Bank and Metropolitan Bank
Phillipine National Bank and Bank of Phillipine Isle
Phillipine National Bank and Rizal Com
China Bank and Metropolitan Bank
China Bank and Bank of Phillipines Isle
China Bank and Rizal Com
Metropolitan Bank and Bank of Phillipines Isle
Metropolitan Bank and Rizal Com
Bank of Phillipines Isle and Rizal Com

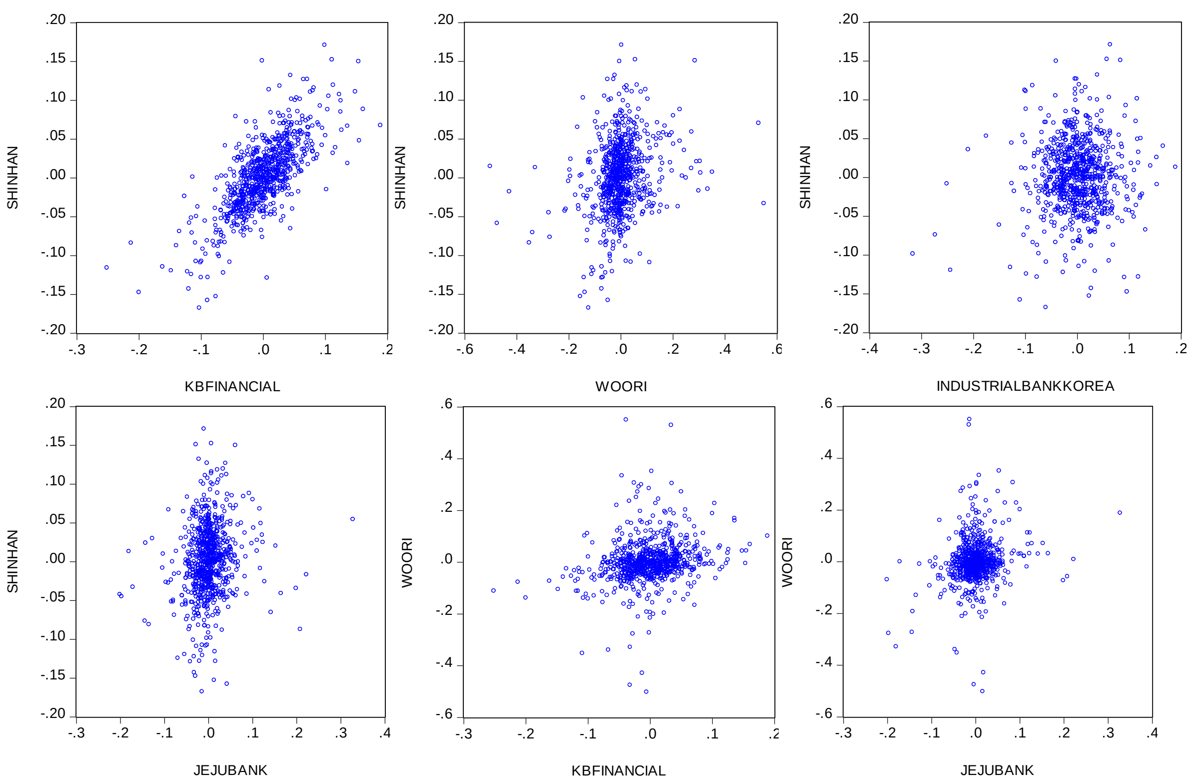
Scatter Plot Singapore Bank Stock Returns

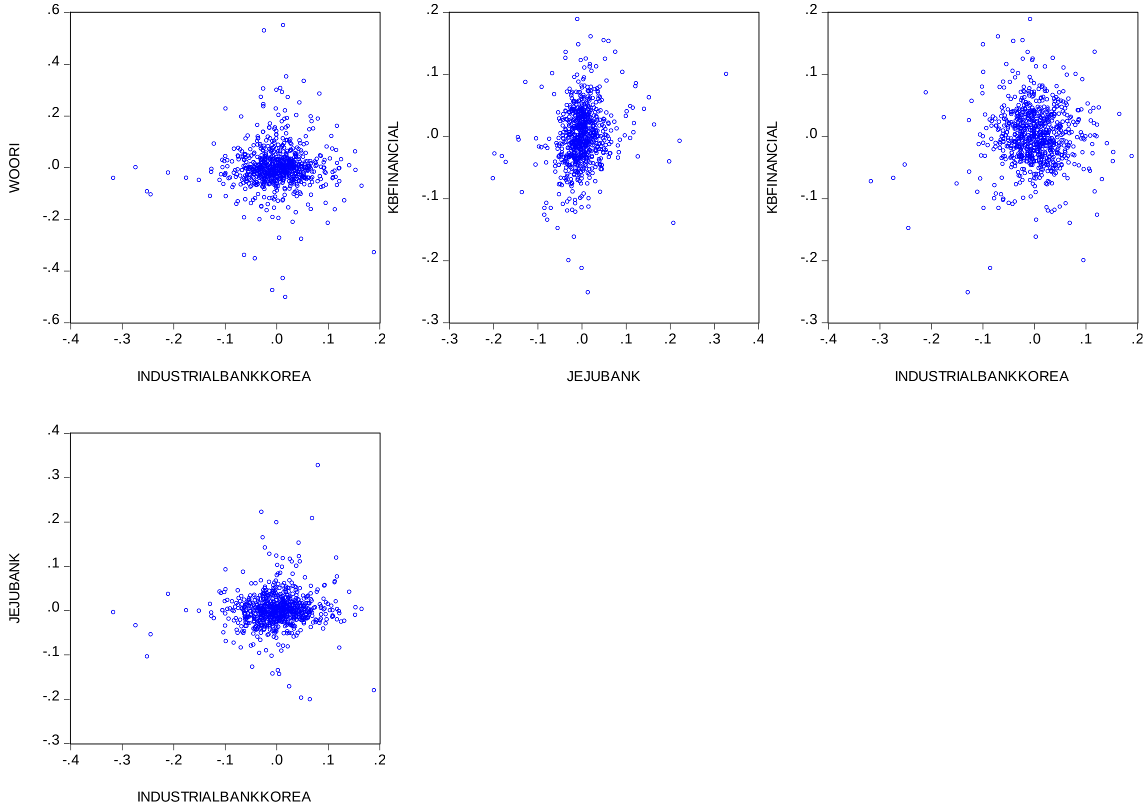


Linkage Estimator Plot: Singapore Bank Stock Returns

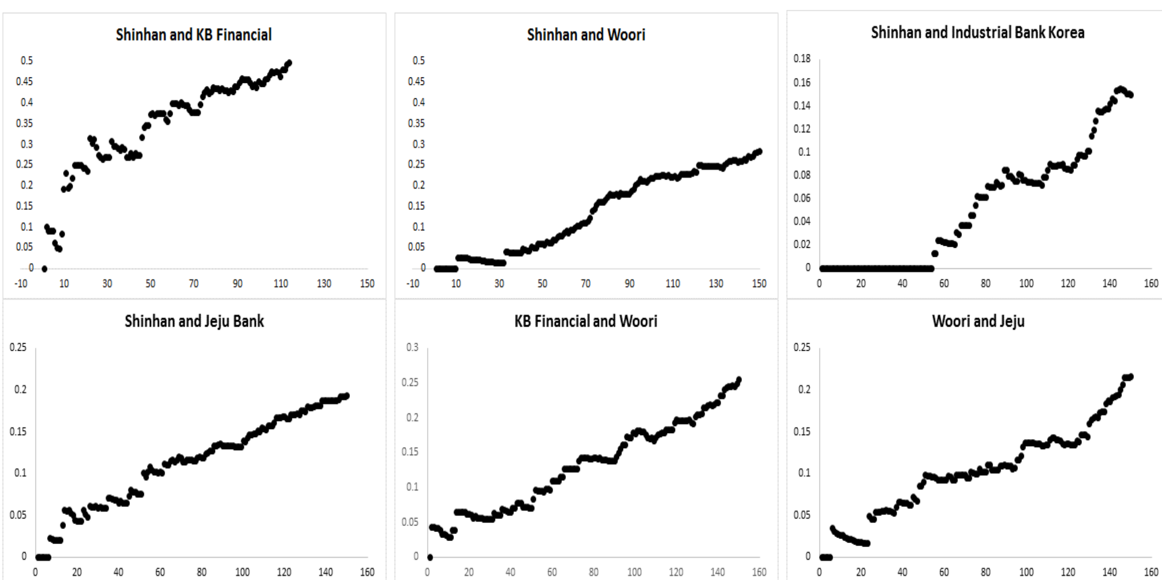


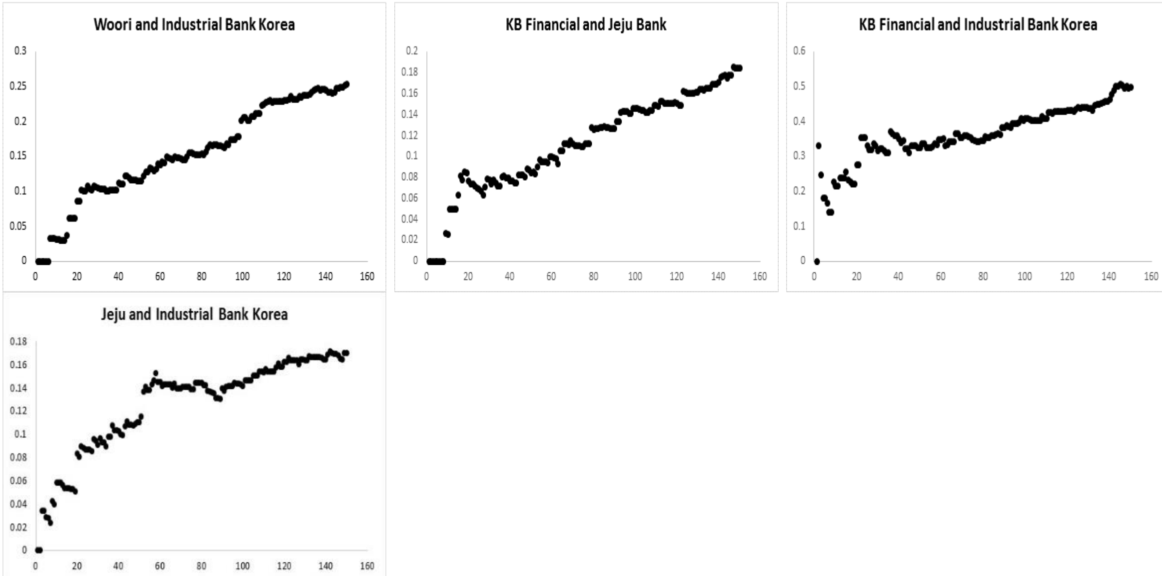
Scatter Plot South Korea Bank Stock Returns





Linkage Estimator Plot: South Korea Bank Stock Returns




Woori and Industrial Bank Korea
0 0.05 0.1 0.15 0.2 0.25 0.3
0 20 40 60 80 100 120 140 160
KB Financial and Jeju Bank
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
0 20 40 60 80 100 120 140 160
KB Financial and Industrial Bank Korea
0 0.1 0.2 0.3 0.4 0.5 0.6
0 20 40 60 80 100 120 140 160
Jeju and Industrial Bank Korea
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18
0 20 40 60 80 100 120 140 160