An assessment of contagion risks in the banking system using non-parametric and copula approaches

Abstract: This study endeavours to shed some light on the Contagion risk in the Vietnamese banking system. In so doing, we analyse the contagion risk through stock returns on listed commercial banks by employing non-parametric and Copula approaches. A rich set of empirical approaches are employed, including non-parametric (Chi-plots, Kendall-plots) and parametric Copula estimations to define the dependence structure of pairs of daily returns, balanced by a total of 36 copulas with 17,456 observations over the period from July 2006 to September 2017. Our results show that the risk of each individual bank may transmit to other banks through stock returns, which are reflected in their price information. The results also suggest existence of contagion risk and strong dependency in the structure of stock returns of banks under analysis. As a consequence, to avoid negative returns for the portfolio, careful diversification is required while investing in the Vietnamese banking sector, when showing a Clayton relationship (left-tail dependency). Our findings have profound implications for investors, policymakers and authorities responsible for financial stability.

JEL Classification: G14, G15, G17

Keywords: Contagion risk, banking sector, non-parametric, Copulas, financial stability.

1. Introduction

An increased level of financial integration comes with higher likelihood of risk and shock transmission to all the institutions integrated into the financial system. This makes it necessary to have an appropriate regulatory regime in place (Mälkönen, 2004; LaBrosse et al.,2011; Lengwiler and Maringer, 2015; D'Hulster and Ötker-Robe, 2015)[1]. This may entail a set of macroprudential rules and policies as well as solvency arrangements, which could limit financial disruptions, in case a systemically important financial institution fails[2]. In order to design appropriate regulatory frameworks, it is vital to account for the dependence structure of contagion risk to avoid the systematic collapse of the financial system if and when a bank or financial institution goes bankrupt. One of the major outcomes of globalisation and financial liberalisation in the last few decades has been that the size of the financial sector and volume of financial transactions have been increasing at a rapid pace.

Emerging markets are following a similar path of financial deepening to the developed world. Stock market capitalisation measures around 10-15% of GDP and there has been substantial growth in credit creation, which is now over 50% of GDP in many emerging economies. This rapid increase in the size of the financial sector makes financial stability more important for the real economy and has sparked debate (See Sahay, et al 2015 for interest insight by IMF's staff). It can be argued that financial stability and economic stability are in fact "two sides of a coin" (Borio, 2011; Nasir et al., 2015). The importance of the financial sector is not trivial nor is recognition of this new. Recognition of the significance of the financial sector for the real economy dates back to Bagehot (1873). Later studies, for instance, McKinnon (1973) and Shaw (1973) argue that lack of financial development limits the amount of savings which could be channelled to profitable investment opportunities[3]. As such, impediments to financial development prevent financial intermediation from channelling useful resources to the most productive sectors of the economy. Clearly, if a stable and growing financial sector promote growth and stability in the real economy then the state of financial sector stability has repercussions and potential financial crisis is a perpetual issue requiring vigilance.

The Global Financial Crisis (GFC) of 2008-09 was a manifestation of strong macro-finance interlinkages revealing an important aspect of the financial sector and institutions: the "contagion effect". In the course of

[1] One can also see Singh and LaBrosse (2011) for an interesting insight into the ingredients necessary for developing a framework for effective financial crisis management.
[2] It is also contested that the risk management in the financial sector, particularly the banking sector faces paradoxes in the form of tensions between market versus regulatory demands (see, Lim et al., 2017).
[3] For a study that has summarised the main channels through which the financial sector can influence economic growth, for instance, producing information; allocating capital to productive uses; monitoring investments and exerting corporate control; facilitating trading, diversification, and management of risk; mobilizing and pooling savings; and easing the exchange of goods and services, see, Levine (2005).

a day, millions of financial transactions are carried out among financial intuitions and market participants across the globe. The high frequency, as well as the magnitude of these transactions, raises the possibility of exposure of participants to any adverse outcome. To be more specific, when one financial institution suffers from an adverse internal or external shock, there are domino effects and the negative effects are transferred to the whole system triggering a financial crisis.

According to Schoenmaker (1996), the risk of contagion in banking is a systemic risk which can be defined as the risk that financial difficulties at one or more bank(s), may spill over to a large number of other banks or to the financial system as a whole[4]. The GFC is a clear depiction of this phenomenon where one adverse event followed another, from the bailout of the British bank Northern Rock to the collapse of Lehman Brothers (see, Blinder 2013 "*After the Music Stopped*" for a detailed insight). The financial crisis and its contagions are chaotic. For example, BNP Paribas described its decision to suspend three funds as an effect of the "*complete evaporation of liquidity*" (BNP Paribas, 2007)[5]. In contagion, each action creates a ripple of consequences, including the collapse of confidence among investors, who in turn rush to liquidate their deposits. Where institutions are highly leveraged the effects are exacerbated.

Contagion risk has spillover effects which make the analysis of contagion important to understand the financial system and its dynamics. This is not to suggest the phenomenon is new. Financial crisis which harbours financial stress with ripple effects has been the focus of a number of studies, particularly since the GFC. Moreover, the history of finance is the history of financial crises and we can track back to 33AD and Tiberius' efforts to use Quantitative Easing to calm financial panics (see, Taylor, 2013). However, a difficulty faced by any endeavour to investigate contagion has been how to carry out an estimation using econometric modelling. A key technical issue has been how to determine how much dependence between two financial entities prevails within a random distribution. Financial markets experience major oscillations during financial crises; the question this raises is: to what extent are oscillations a result of systemic or intrinsic characteristics of the market or financial intuitions? There have been several attempts to explore the dependency among financial institutions using traditional approaches [such as Granger causality test; Vector Auto Regression (VAR)]. However, these have been prone to criticism due to problems with strict assumptions around the probability distribution, as well as compatibility of the underlying dataset[6].

[4] Also see Ullah et al (2019) for an insight into risk perceptions and risk management approaches.
[5] Specifically, the BNP Paribas Investment Partners suspended the calculation of the Net Asset Value of three of her funds including Parvest Dynamic ABS, BNP Paribas ABS EURIBOR and BNP Paribas ABS EONIA.
[6] For instance, specific to the Granger-causality test, it requires a set of variables that characterizes zero constraints on the autoregressive coefficients (Lütkepohl, 1991). Sometimes, we are required to know the distribution of these variables (usually asymptotic chi-square distribution, see, Lütkepohl and Reimers 1992) before we perform analysis. Granger-causality and the VAR tests do not capture the exact dependence structure (e.g. tail-dependence). On the other

In the Post-GFC era, where emerging markets have been the engine of global growth, these markets have also progressed in terms of the development of their financial sector (Sahay et al., 2015). The Vietnamese economy and financial sector have, for example, demonstrated remarkable growth. Since the start of this century, the real economy has grown at an annual rate varying between 5.2% and 7.5 % (World Bank, 2017)[7]. Liberalization of the economy and positive policy initiatives have facilitated investment in the real economy. The economy has also experienced financial deepening facilitated by a series of reforms and financial liberalisation (Bloomberg, 2016). Foreign investors have opened approximately 1.3 million accounts with a foreign portfolio of approximately US$13 billion (Sam Ta, 2015). Vietnam participates in the World Trade Organization, Trans-Pacific Partnership Agreement negotiation and the ASEAN Economic Community. Concomitantly, the stock market has experienced growth. The capitalization of the Vietnamese stock market grew to US$52 billion (approx. 32% GDP) in 2017 (the bond market constitutes about 17% of GDP). The stock market yielded an annual return of 17.1% in 2016, and around 12% through 2017 (Nguyen, 2017). The Vietnamese economy is on the road to further integration and liberalisation, which provides a rationale to explore the Vietnamese financial sector and particularly its banking sector in the context of future financial stability[8].

It is prima facie evident that poor institutional quality (e.g. corruption, bureaucracy) and problems of governmental control (e.g. public sector domination, interventions.) cause distortions in the smooth functioning of the banking system. The increase in non-performing loans, unexpected volatility of interest rates and many instances of fraudulent activities can hamper banking sector firms. These factors contribute to risks for a specific institution as well as the banking system in general. In that context, it is vital to understand the dynamics of the contagion risk in the Vietnamese Banking System. To address this issue, in this study we explore the dependence structure of the Vietnamese banking system. In so doing, we employ two innovative methodological approaches, non-parametric (Chi-plots and Kendall-plots) and Copulas estimations (Gumbel, Clayton and Normal). These approaches are novel and are the outcome of recent developments in mathematical and econometric techniques rather than traditional time-series evaluation. The application of these innovative approaches provides a contribution to the literature on the estimation of contagion risks faced by financial institutions, especially banks. We also employ a rich dataset of paired

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hand, Copulas can be applied for random variables without determining their distribution. In addition, they define the left-tail dependence structure as risk; hence, it can be better than the traditional approach (Mesfioui et al., 2008).

[7] The Vietnamese economy also seemed to be one of the best-performing economies for 2017 with an annual growth figure of 6.81%.

[8] For further details on the socio-economic development of Vietnam, please refer to the World Bank Country level Indicators available at https://data.worldbank.org/country/vietnam.

daily returns, balanced by 36 couples with 17,456 observations over the period starting from July 2006 to September 2017.

Our key findings suggest that the risk for each individual Vietnamese bank could transmit to other banks through stock returns, which are reflected in their price information. The results also show significant evidence of the existence of contagion risk and strong dependency in the structure of returns of underlying listed banks. As such, in investing in the banking sector, a diversification strategy should account for the Clayton relationship (left-tail dependency) to avoid negative return for the portfolio. Our findings have profound implications for investors, policymakers and authorities responsible for financial stability.

The paper proceeds as follow; Section 2 reflects on the existing evidence on the subject of contagion; Section 3 sets out the empirical framework and non-parametric and Copula approaches as a means to test the dependence structure of the Vietnamese banking sector; Section 4 presents the results of analysis and findings; Section 5 draws conclusions and discuss policy implications.

2. Contagion Risk

Contagion risk in the financial sector has been a focus of attention of several scholars. Financial panics followed by a collapse of confidence leads to bank run and a race to liquidate assets, similar in rationale to a race to the bottom in a financial meltdown. The severity of such a panic was well recognised by Bagehot (1873) as reaction to the 1866 financial crisis in the London banking industry. This led him to argue that "to *avert panic, central banks should lend early and freely (i.e. without limit), to solvent firms, against good collateral, and at 'high rates'*" (Tucker, 2009, p. 3). In a financial panic, the central bank acts as a "*Lender of Last Resort*". The intention is to create a circuit breaker which forestalls further panic in the system as a whole[9]. Contagion risk in the banking sector, risks the failure of financial institutions via overwhelming withdrawals of cash by creditors and customers (Scott, 2016). Contagion involves domino effects and affects all market participants. In this scenario, the optimal strategy for a depositor is to liquidate deposits sooner than other depositors. This herd behaviour may make even a solvent bank insolvent. The seminal work of Diamond and Dybvig (1983) explores the structure of this behaviour. Benston (1986) and Postlewaite and Vives (1987) build on this approach. However, though the systemic importance of failure of a single financial institution is well-recognised a run also has systemic effects, and these are underappreciated in the empirical

[9] Saunders (1987) indicates that contagion risk in the banking system is reduced when the US Federal Reserve establishes its role in preventing bank run and acts as the last lender in capital markets.

literature (Bagehot, 1873; Minsky, 1974; Kindleberger, 1978; Minsky, 1992 and later Cassidy, 2008). There is more that might be said of contagion risk as an issue for financial stability.

"In wild periods of alarm, one failure makes many, and the best way to prevent the derivative failures is to arrest the primary failure which causes them." Bagehot (1873, p.51).

Among the empirical studies which reflect on contagion risk in the banking sector, Ong et al. (2007) test the likelihood of shocks from British systemic banks on large local and foreign counterparts and vice versa. They find that contagion risk among banks exhibits "home bias" as the individual banks are affected differently by idiosyncratic shocks to their major counterparts and banks have been affected differently by common shocks to the real economy or financial markets. Furthermore, bank "soundness" appeared to be more susceptible to common shocks when the global financial and economic environments were turbulent. Ong et al's results show that when one bank suffers a substantial decline in stock price the cause relates mainly to a downturn in another intermediary banking entity (and so a "contagion risk"). The Ong et al (2007) study is UK focused. A number of studies, for instance, Grossman (1993), Hasan and Dwyer (1994), Kaufman (1994) and Schoenmaker (1996) found that there is contagion risk in the US banking system. Here, in the absence of interventions by the authorities, initial failure of the bank could generate further failures. This implies an important role for the central bank as the lender of last resort. Schoenmaker (1996) argues that the contagion effects of bank runs need to be treated explicitly in a model of banking panic.

There are two channels through which contagion can spread; these are the information channel and/or the credit channel. Aharony and Swary (1983) argue that in the information channel there is an important distinction between pure (industry-specific) contagion and noisy (firm-specific) contagion, and this needs to be accounted for. Pure contagion occurs when negative information, for instance, fraud or losses on specific risky investment with regards to one bank, adversely affects all other counterparts, including those that have nothing in common with the first bank. Noisy (firm-specific) contagion occurs if the failure of a bank reveals bad (yet noisy) signals regarding other banks which share common characteristics. Here, in case of failure of one bank, the other banks which hold a balance sheet of similar assets and liability structure can also be prone to similar adverse shocks and could face a run[10]. The second channel through which the contagion can spread is the credit channel; constituting a web of linkages between banks in financial markets, including the interbank funding market, the over-the-counter (OTC) derivatives market and the payment systems. A solvent bank can subsequently fail if it has substantial claims on the already failing bank. The lack of

[10] As stated by Schoenmaker (1996, p.89) "In a world with imperfect information, runs on other banks can be triggered by perceived - and thus not necessarily actual similarities - with the failing bank."

information on interbank exposures can lead to further loss of confidence among market participants. In a recent study focusing on the Euro-zone, Kosmidou et al (2017) analysed whether asymmetric information (opacity), importance (network centrality) of the banking sector and systemic risk (clustering) play significant roles in the evolution of stock crashes in the banking sector. Their results show that under certain conditions, these factors do matter for banking sector stock.

There are several studies which analyse the contagion risk in the financial sector from a single country perspective, which consider other characteristics. These studies focus on factors such as a financial crisis or business cycles. Forbes and Rigobon (2002), as well as Dungey et al. (2005) focus on co-movements and interdependence of financial markets. Recent studies on these follow similar analytical frameworks and focus on the co-movement and interdependence of financial markets, for instance, Aloui et al. (2011); Kenourgios et al. (2011) ; Kenourgios, Samitas and Paltalidis (2011) ; Samarakoon (2011) ; Bekaert et al. (2014); Baur (2012); Hwang et al. (2013); Nasir and Du (2017); Huynh and Burggraf (2019). However, without downplaying the importance of these studies, it is important to emphasise that co-movement is not necessarily identical to the contagion. This has been discussed at length by Scott (2016) in his seminal recent book "*Connectedness and Contagion*". Scott (2016) argues that it is not connectedness but contagion that is the most significant element of systemic risk faced by the financial system. In its true essence, contagion is an indiscriminate run by short-term creditors of financial institutions that can render otherwise solvent institutions insolvent. In this study, we draw on Scott's reasoning - accounting for the subtle demarcations between connectedness and contagion.

As noted, previous empirical studies have been focused on traditional statistical approaches (for instance, Granger causality and VAR frameworks). These estimate "connectedness", a point acknowledged by Dungey et al. (2005, p.2):

> [D]ifferences in the definitions used to test for contagion are minor and under certain conditions are even equivalent. In particular, all papers are interpreted as working from the same model, with the differences stemming from the amount of information used in the data to detect contagion. Interpreting the approaches in this way provides a natural ordering of models across the information spectrum with some models representing full information methods and others representing partial information methods.

Similarly, Markose (2013) advocates "*holistic visualization and modelling techniques"* to better understand the Systemic risk faced by financial intermediaries. Yet, despite this in the above-cited literature, the focus has been on the traditional time-series models. Dependence on the characteristics of normal distribution and time length of observations has limited the view of the analysts. In order to overcome this problem, in this study, we employ two innovative methodological approaches which include non-parametric (Chi-plots and Kendall-plots) and Copula estimations (Gumbel, Clayton and Normal). These approaches are novel and the outcome of recent developments in mathematical and econometric methods rather than traditional time-series evaluation.

There are a number of studies that have used Copulas for estimation of dependence structure such as Hui (2005) ; Boubaker and Salma (2011) ; Ye et al. (2012); Bhatti and Nguyen (2012); Chen et al. (2014) ; Zhang and Li (2014). However, these studies have oriented on financial market indices and their co-movements while mostly focusing on the aggregate stock market data. In terms of inclusive treatment and assessment of contingent risk, we need to distinguish financial institutions (banks) with different characteristics. In this regard, the returns on a particular stock carry important firm-specific information. Contagion risk is idiosyncratic in the banking sector. With this in mind, we now move on to quantify contagion risk in the Vietnamese banking system.

3. Research Methodology

We employ Copulas as well as a Non-Parametric (Chi and Kendall) Plots approach. The copulas are constructed on Sklar's theorem, an n-dimensional copula $C(u_1,\ldots,u_d)$ is a multivariate distribution function in $[0,1]^d$. This function requires that the marginal distribution (u_i) is to be uniform ranging from [0,1] interval. In addition, Sklar(1959) shows a link between multivariate distribution functions and their marginal distribution functions. Hence, any joint distribution $H(x_1,\ldots, x_d)$ can be related to the marginal distributions $F_1(x_1),\ldots, F_d(x_d)$ by an appropriate Copula C:

$$H(x_1,..,x_d) = C(F_1(x_1),\ldots,F_d(x_d))$$

The Copulas density c can be obtained by differentiating the aforementioned equation; thus, we get:

$$c\big(F_1(x_1),\ldots,F_d(x_d)\big) = c(u_1,\ldots,u_d) = \frac{\partial^d(u_1,\ldots,u_d)}{\partial u_1,\ldots,\partial u_d}$$

If F(x, y) is a joint density function with margin function F(X) and F(Y). Hence, there exists one Copula for all $x, y \in [-\infty,+\infty]$ which is F(x,y) = C(FX(x),FY(y)), (see Nelsen (2006). In the recent development on

Copulas, Huynh et al. (2018) argued that Copulas called C exist only if X and Y are continuous random variables completely meeting the previous requirements. The Copulas C of these continuous random variables must strictly comply with a form of increasing transformations of the marginal distribution of F(X) and F(Y). Copulas provide wide scope for statistical applications. In this paper, we only exploit them as a tool to determine the dependence structure of variables, which range into three popular families Gumbel, Clayton and Normal.

With regards to Gumbel Copulas, which is known as the right tail dependence. Huynh et al. (2018) indicated that Gumbel Copulas can be estimated by

$$C_\theta(u,v) = e^{-[(-lnu)^\theta + (-lnv)^\theta]^{\frac{1}{\theta}}}$$

where $\phi(t) = (-lnt)^\theta, \theta \geq 1$ with the level of dependence in left-tail (λ_L) and right tail of (λ_U): $(\lambda_L) = 0, (\lambda_U) = 2 - 2^{\frac{1}{\theta}}$. This family of Copula captures the upper tail dependence with the indicator (λ_U) for the previously mentioned dependence.

Clayton Copulas provide a means to capture left-tail dependence for "risk contagion". The studies by Huynh et al. (2018) and Huynh (2019) state:

$$C_\theta(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{\frac{-1}{\theta}} \text{ và } C_0(u,v) = \Pi = uv,$$

In which, $\phi(t) = \frac{t^{-\theta}-1}{\theta}, \theta \geq 1$ with the left-tail (λ_L) and the right-tail (λ_U): $(\lambda_L) = 2^{\frac{-1}{\theta}}, (\lambda_U) = 0$. This family of Copula captures the lower tail dependence with the indicator (λ_L). Related to Normal Copulas, this family does not capture the upper or lower tail and this parameter stays in the range of $(0 \leq \theta \leq 1)$

$$C_\theta(u,v) = \int_{-\infty}^{\phi^{-1}(u)} dx \int_{-\infty}^{\phi^{-1}(v)} dy \frac{1}{2\pi\sqrt{1-\theta^2}} \exp\left\{-\frac{x^2 - 2\theta xy + y^2}{2(1-\theta^2)}\right\}$$

Table 1. Copulas for Estimation of Parameters and Structure Dependence

Name	Copulas	Parameter	Structure dependence
Gaussian	$C_N(u,v;\rho) = \phi(\phi^{-1}(u), \phi^{-1}(v))$	ρ	No tail dependence: $\lambda_U = \lambda_L = 0$

Clayton	$C_{rC}(u,v;\theta) = C_C(1-u, 1-v;\theta)$	θ	Asymmetric tail dependence: $\lambda_U = 0, \lambda_L = 2^{-1/\theta}$
Gumbel	$C_G(u,v;\delta) = exp\left(-\left((-\log u)^{\delta} + (-\log v)^{\delta}\right)^{1/\delta}\right)$	$\delta \geq 1$	Asymmetric tail dependence: $\lambda_U = 2 - 2^{1/\delta}, \lambda_L = 0$

Source: Jin (2017)

We employ Copula approaches to estimate the dependence structures to gauge the contagion risk effect of each pair of banks in Vietnam. However, we mainly focus on the tail dependency that demonstrates simultaneous losses or gains.

Table 2. Non-Parametric (Chi and Kendall) Plots for Determining Dependence Structure

Name	Formula
Chi-plots	Chi-plot is based on the ranking of data and it is also graph to illustrate the spread over a wide area (λ_i, χ_i) for the movement by both variables in couple of (X_i, Y_i) with i = 1, 2…n Assume that H_i is the joint distribution function between two continuous variables and F_i, G_i is the marginal function for X and Y, respectively with showing in point of data hereinafter: $$H_i = \sum_{j \neq i} I(X_j \leq X_j, Y_j \leq Y_i)/(n-1)$$ $$F_i = \sum_{j \neq i} I(X_j \leq X_i)/(n-1)$$ $$G_i = \sum_{j \neq i} I(Y_j \leq Y_i)/(n-1)$$ In which, I(A) = 0 or 1, which depends on the event by A becoming true or false. Fisher and Switer suggest to draw (X_i, Y_i) by the calculation as follows: $$X_i = \frac{H_i - F_i G_i}{\sqrt{F_i(1-F_i)G_i(1-G_i)}}$$ $$\lambda_i = 4S_i \max\left\{\left(F_i - \frac{1}{2}\right)^2, \left(G_i - \frac{1}{2}\right)^2\right\}$$ In which, $S_i = sign\left\{\left(F_i - \frac{1}{2}\right)\left(G_i - \frac{1}{2}\right)\right\}$

	The graph by chi-plot has the confidence interval, which receives value by $\pm c_p/\sqrt{n}$ (approximate at Cp at the significance level 95%, which is nearly 1.78). The (λ_i, χ_i) from the independent variables and continuous has tendency to stay in the same line. For the positive marginal dependence, the couple of (λ_i, χ_i) has a trend of spreading out the line above.
Kendall-plots	K-plot or called Kendall-plot is based on the ranking of data, which are collected by Quantile-Quantile-plot (QQ-plot) to test the normal features. The couple of data (X_i, Y_i) will transform into $(W_i : n, H(i))$ with i = 1, 2…n. Furthermore, the value of H(i) is defined as follows: $$W_i{:}n = \omega k_0(\omega)\{K_0(\omega)\}^{i-1}\{1 - K_0(\omega)\}^{n-i}d\omega$$ But it has to satisfy the requirements here: H(i) < … < H(n). Interestingly, $W_i{:}n$ is the expected statistical value in ranking i from the random sample W= C(U,V) = H(X,Y) for the size with n (observations). With the null hypothesis H_0, U and V (or called X and Y) are independent variables. The value of W_i: n is calculated by the formula above. In which, $$K_0(\omega) = \text{P(UV} \leq \omega = \text{P}\left(\text{U} \leq \frac{\omega}{v}\right)dv = 1dv + \frac{\omega}{v}dv = \omega - \omega\log(\omega)$$ Then, k_0 is the relative density.

Source: Nguyen et al. (2017); Huynh (2018) and Huynh (2019).

In summary, both chi-plot and K-plot (or Kendall-plot) are used to define the dependence structure of the independent variables; it is appropriate to choose the well-matched tail dependence of each Copula family. As the test applied is asymptotic, its efficiency is related to the sample size. The availability of high frequency and large enough samples is not an issue and usage of larger sample size is possible. We, therefore, collected daily data. For estimation of Kendall-plots, Chi-plots and three families of Copula, the codes are programmed using the R Software[11].

3.2 Data

Daily stock price data from July 2006 to September 2017 was obtained for nine of the largest banks listed on the Vietnamese stock exchange (including Ho Chi Minh City and Hanoi). We removed days with no

[11] The program codes are available from the corresponding author on request.

transactions on the stock exchange to create a balanced dataset, prior to employing the Copulas to estimate dependence structures. In addition, the collected data were adjusted for bank information, such as the dividend or any circumstance influencing stock price. Our dataset of 17,456 observations for all banks is sufficient to facilitate testing by the Copulas approach. In order to calculate the dependence structure, we apply Miller's (2013) approach to determine the stock return as follows:

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

Where P_t is the current and P_{t-1} is the previous period price of listed bank shares. We remove biased figures as required. To be specific, we excluded daily data with no transaction. In addition to Saturday and Sunday, all (bank) holidays are eliminated from our data in order to achieve a balanced dataset for estimation. This was a crucial step, since Copulas estimation only runs when the dataset is balanced.

4. Analysis and Findings

4.1 Descriptive Statistics

We performed a descriptive statistical analysis to gain insight into the features and distributional characteristics of our data on commercial Banks. The results are presented in the following Table 3: -

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
BID	0.0003	0.0204	-0.0723	0.0674	0.3466	5.3611
CTG	-0.0001	0.0193	-0.0716	0.0674	0.2707	4.4706
EIB	-0.0001	0.0170	-0.0717	0.0676	0.2108	6.1296
MBB	0.0006	0.0146	-0.0645	0.0659	0.3979	5.7673
STB	-0.0003	0.0223	-0.0960	0.0891	0.1787	3.7689
VCB	0.0002	0.0201	-0.0715	0.0676	0.1282	4.0623
ACB	-0.0001	0.0220	-0.1231	0.1191	0.0868	7.2661
NVB	-0.0002	0.0354	-0.1053	0.0953	0.0813	3.8746
SHB	-0.0004	0.025	-0.1631	0.0944	0.1267	5.0025

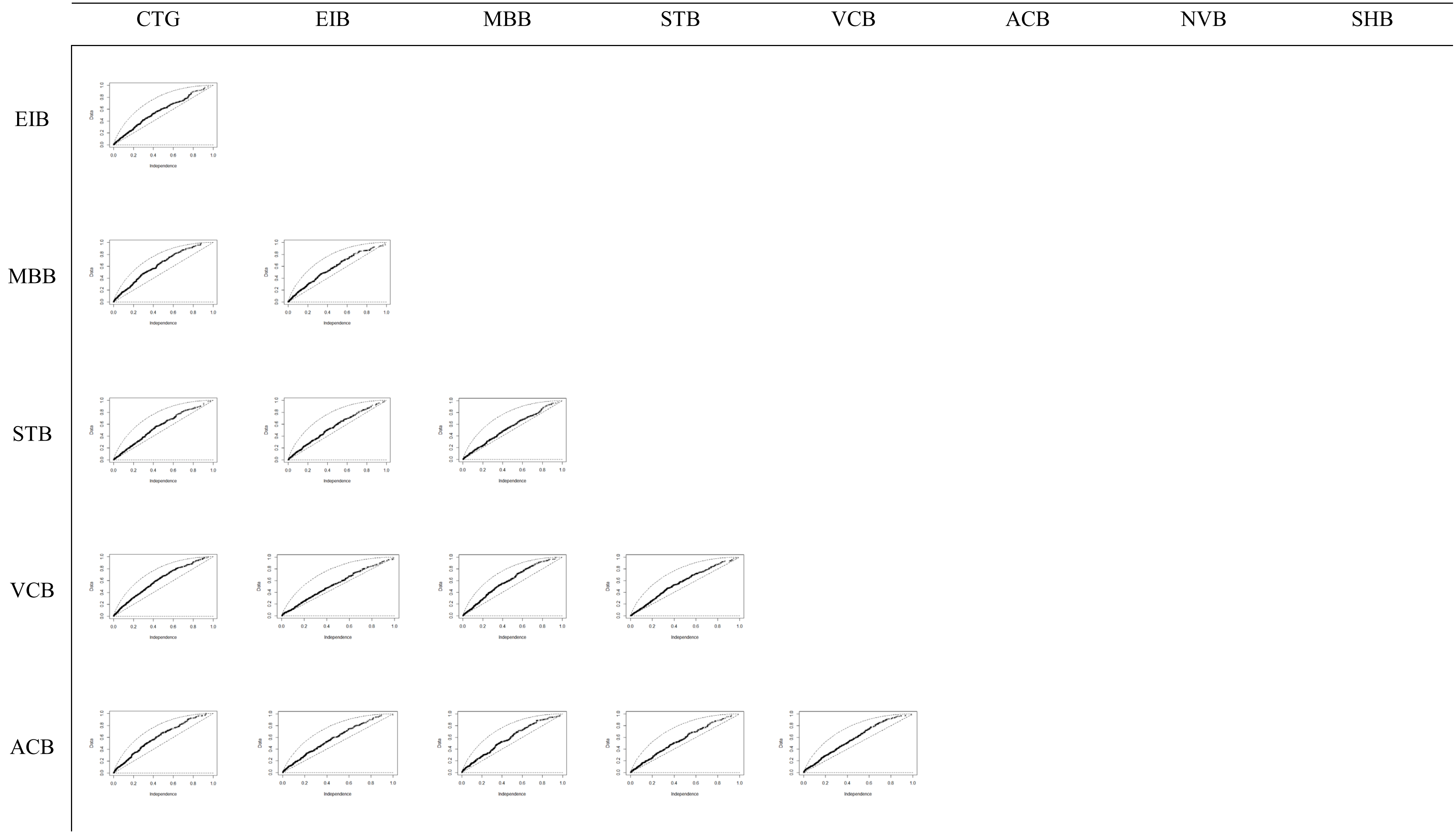
The descriptive statistics presented suggest that despite some subtle differences in the values, on the whole, returns did not show much heterogeneity in their distributional features. An important aspect to consider at this juncture is that according to Sklar's (1959) theory, the estimation of Copulas is only applied to a symmetric dataset and quantities of observations. To achieve this, we divided each variable into 36 pairs of banks to accurately match the time horizon. In general, we observed that the mean return of these banks are nearly zero whereas the standard deviations ranged from 1.4% to 3.5%. The minimum and maximum value of return are also appropriate with the time horizon of this study (over the Global Financial Crisis 2007-8 and later recovery period). However, it is significant that data are positively skewed. The implication is that magnitude has increased considerably over the 11 years. Most variables have lepto-kurtosis with over standard kurtosis. It could be concluded that they have fat-tail distribution and they may suffer sudden losses in probabilities. To be more specific, MBB obtains the highest return while NVB obtains the lowest. Nevertheless, MBB has the lowest standard deviation, which represents low fluctuation in returns. In contrast, NVB has the highest volatility of return[12].

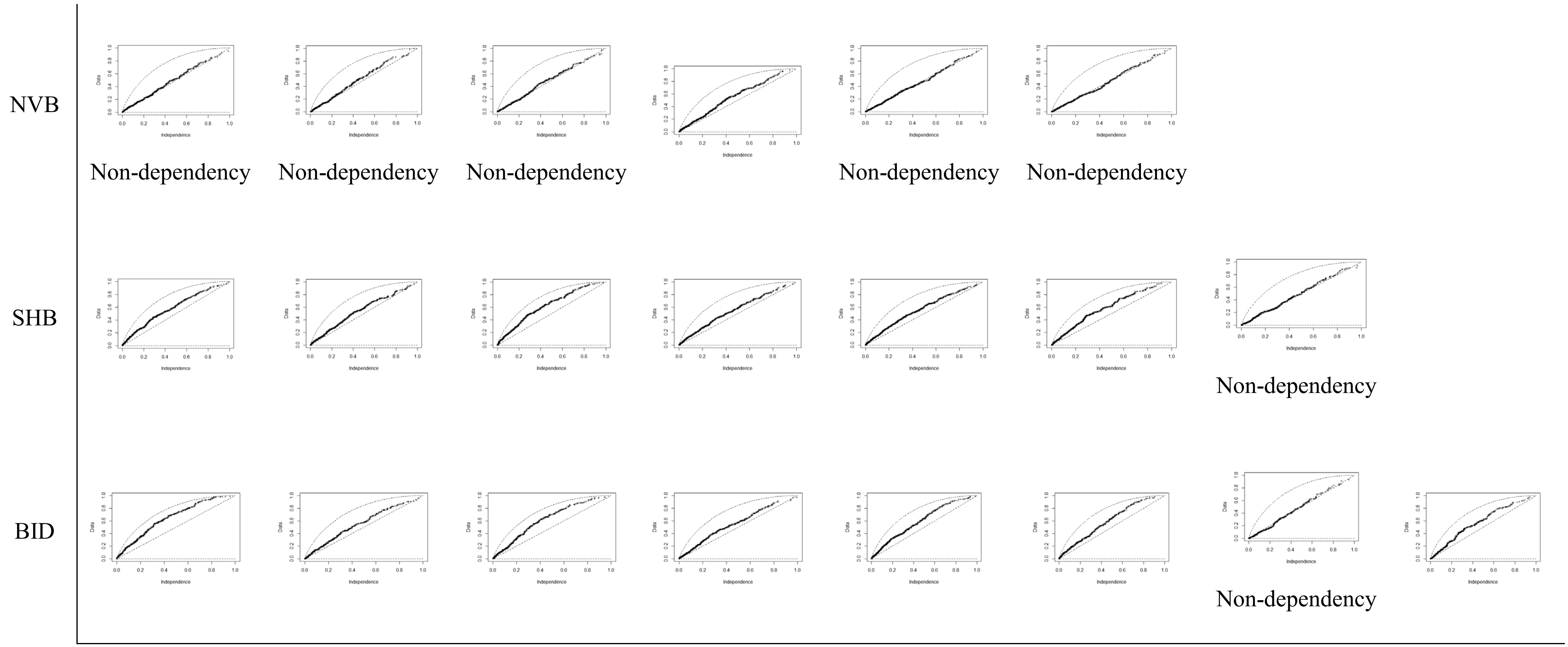
4.2. Non-parametric plots

After descriptive statistics, we applied Non-parametric analysis, starting with Kendall-plots to estimate the dependence Structure. The results are presented in Figure 1:

[12] This is a manifestation of Markowitz's (1991) argument on risk and return.

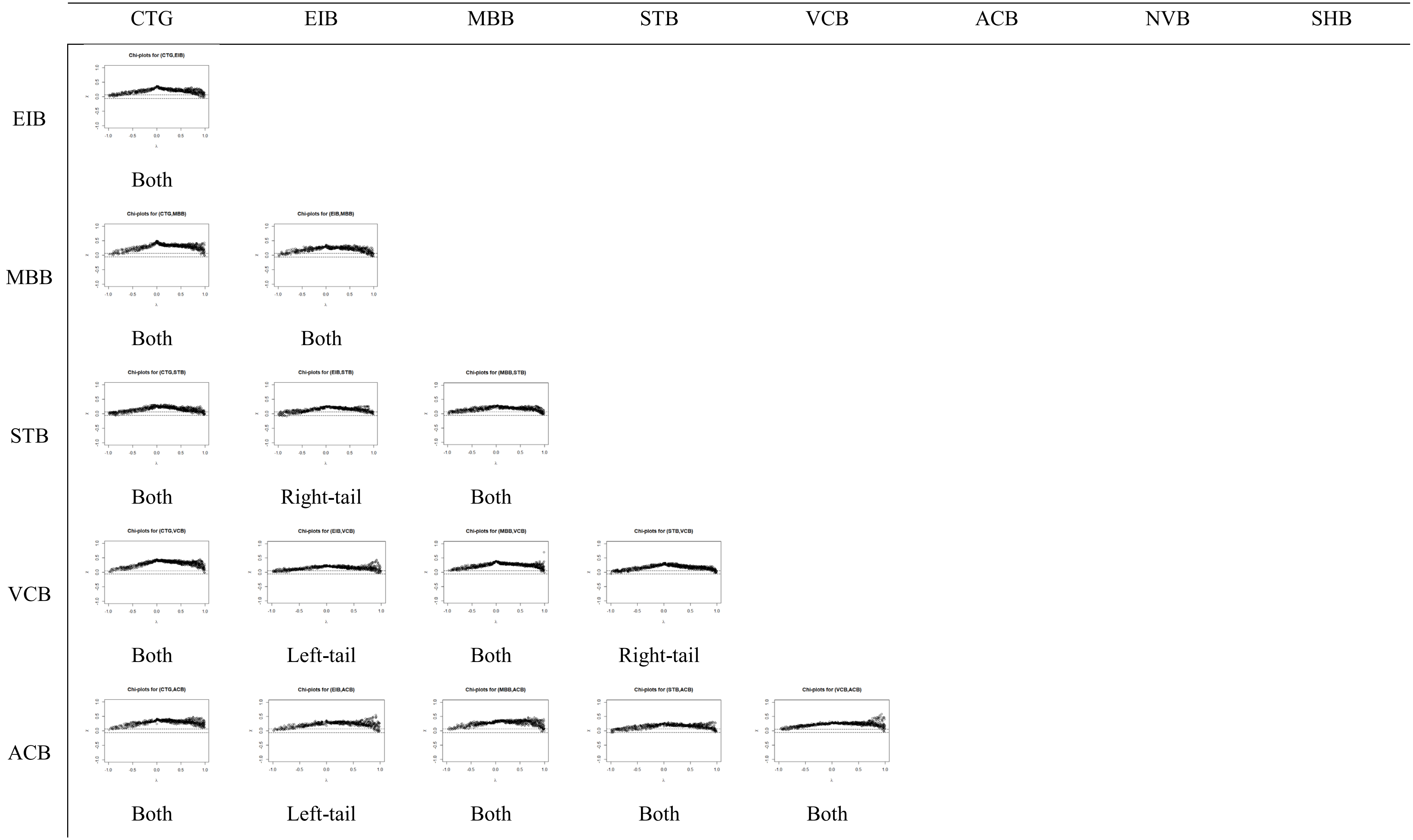
Figure 1. Kendall-plots for estimation Dependence Structure

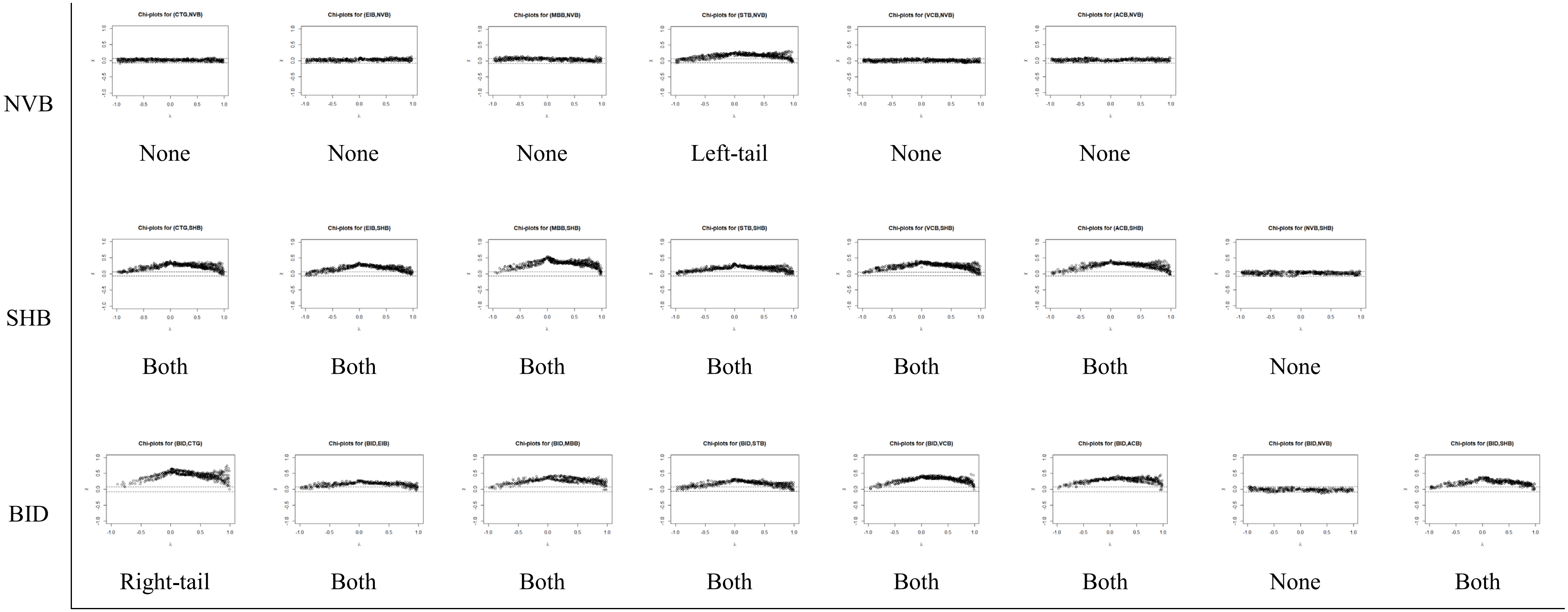




The K-plots indicate that there is an inter-relationship between two random and continuous variables: bank stock's return. This can be noticed if the illustrated points do not lie along the 45-degree diagonal line at the tail of the graph. One can conclude that these variables have mutual structural dependence. In our case, the results from Figure 5 clearly show that there are strong associations and dependencies between these Banks, witnessed in the divergence of dependence structure from the diagonal line. However, one important point to be considered here is that the Kendall plots only represent that these random and continuous variables have structure dependency. They do not provide much insight and indication regarding which tail is strongly interconnected with the other. In order to further investigate and determine the tail-dependence and before drawing a conclusion on contagion risk in the Vietnamese banking system, further tests are required. For this reason, we estimated the Chi-plots for the Dependence Structure of distributional tails. The results are presented in Figure 2:

Figure 2. Chi-plots for estimating dependence structure on tail





(Source: The authors' estimation using R)

In the Chi-plots, we analyse the tail dependence based on the density of plotted points on the marginal line. Where they lie more on the outside, we conclude they will depend on the corresponding side. The results are shown in Figure 6 which clearly indicate that bank returns have tail-dependence as the vast majority of distribution points were plotted beyond the control lines (+/- 0.05). This is an important finding in terms of dependence structure of banks. This leads us to explore this phenomenon further by employing the Copula (parametric) framework in the second phase of analysis.

4.3. Copula Estimations

In the second stage of analysis, we employed a Copula approach to estimate the Kendall-tau (Kendall-τ). We based our choice of appropriate Copulas on the seminal work of Forbes and Rigobon (2002); Genest and Favre (2007); Grégoire et al. (2008) and Reboredo (2011). Before choosing, which are most appropriate, we performed the goodness-of-fit test for Copulas. This criterion of best fit informs choice of appropriate Copulas to confirm the dependence structures. The copula function is chosen based on the highest log-likelihood value for their characteristics (gain, loss or normal with Gumbel, Clayton and Normal Copulas, respectively). At first, we estimate Kendall-τ parameter to define how much these variables depend on their counterpart regarding structure with the significance level of 1%.

Table 4: Kendall-τ for Determining Dependence Structure

	CTG	EIB	MBB	STB	VCB	ACB	NVB	SHB
EIB	0.271***							
MBB	0.384***	0.278***						
STB	0.221***	0.202***	0.234***					
VCB	0.400***	0.198***	0.324***	0.239***				
ACB	0.376***	0.303***	0.347***	0.212***	0.289***			
NVB	0.028	0.036	0.067	0.212***	0.023	0.028		
SHB	0.307***	0.253***	0.423***	0.232***	0.331***	0.344***	0.0323	
BID	0.546***	0.222***	0.357***	0.248***	0.392***	0.363***	-0.019	0.29***

The hypothesis is $\begin{cases} H_0: \tau_B = 0 \\ H_A: \tau_B \neq 0 \end{cases}$.

(***), (**), (*) reflected statistically significance of the corresponding coefficients at 1%, 5% and 10% level.

The results suggest that pairs of Vietnamese listed banks are mostly inter-dependent at a statistical significance level of 1% (i.e. 29 out of 36 pairs). Hence, we can conclude that the Vietnamese banks are strongly interconnected to each other, which is also reflected in the way the market views them. This interconnectedness can be attributed to and explained by the "cross-owning" phenomenon. If there is any shock from one bank, the others will be influenced through this link. Only NVB (known as Nam Viet Bank, changed the name into National Citizen Commercial Joint Stock Bank) has less dependence on the structure of the remaining banks[13]. Interestingly, this bank is a rural bank, which aims to focus on the agricultural

[13] This is one of the weakest banks in the Vietnamese banking system which was forced to restructure under State Bank of Vietnam's guidance without any cross-owned case for the rest of the banks.

sector. Other banks in our study do not have a lot of transaction with NVB during their operations. It is intuitively the case that they do not show much dependence on NVB. This also confirms the logical robustness of our employed approach.

Secondly, we use the goodness of fit to test how these models are fitted for further estimation. Hence, the hypothesis is $\begin{cases} H_0: C \epsilon C_0 \\ H_A: C \notin C_0 \end{cases}$ with C_0 is a specific Copulas.

Table 5: Goodness-of-fit for Copulas estimation

	CTG	EIB	MBB	STB	VCB	ACB	NVB	SHB
EIB	Reject***							
MBB	Reject***	Reject***						
STB	Reject***	Reject***	Reject***	Reject***				
VCB	Reject***	Reject***	Reject***	Reject***	Reject***			
ACB	Reject***	Reject***	Reject***	Reject***	Reject***			
NVB	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***		
SHB	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	
BID	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***

(***), (**), (*) reflected statistically significant of the corresponding coefficients at 1%, 5% and 10% level.

The results presented in Table 8 suggest that the null hypothesis was rejected in all the cases. An important point we acknowledge here is the critique of the goodness of fit as a benchmark. Embrechts (2009) argues against the use of goodness of fit as a measure. They note that up to 99.9% of Copulas approach will pass through the goodness of fit testing. With this in mind, for robustness purposes, we test which family of Copulas fit for each pair by using Log-likelihood criterion based on the largest score.

Figure 6. Selection of Copulas for each pair

	CTG	EIB	MBB	STB	VCB	ACB	NVB	SHB
EIB	0.3838^{+}							
MBB	1.5525^{+}	0.3993^{+}						
STB	0.2962^{+}	1.2185^{+++}	0.3500^{+}					
VCB	1.6136^{+}	0.4927^{++}	0.4932^{+}	1.2742^{+++}				
ACB	0.5690^{+}	0.7384^{++}	0.5290^{+}	0.3015^{+}	0.4598^{+}			

NVB	0.0697^{++}	1.0478^{+++}	0.1172^{+}	0.3015^{+}	0.0331^{+}	0.0593^{+}		
SHB	0.4471^{+}	0.3450^{+}	0.6055^{+}	0.3319^{+}	0.4820^{+}	0.4924^{+}	0.0600^{+}	
BID	2.1155^{+++}	0.3351^{+}	0.5388^{+}	0.3456^{+}	0.5714^{+}	0.5546^{+}	-0.0364^{++}	0.4242^{+}

Note: ($^{+}$) Normal Copulas, ($^{++}$) Clayton Copulas, ($^{+++}$) Gumbel Copulas.

Based on the parametric estimation of Copulas, we find that there is some left-tail dependence (Clayton branch) on bank stock's return as contagion risk. It can be inferred that the probabilities of simultaneous losses of these banks are quite high. To be more specific, if one bank has a shock with a downward trend in stock price, counterparts will also suffer from such a shock and declining values of stock. Interestingly, for most pairs of banks, returns are dependent on normal shape. This means that the probability of loss and gain is equally divided into two parts of the tail. In addition, there are several pairs of bank stock return, which are chosen to be Gumbel Copulas, which represents high probability of simultaneous gain.

5. Conclusion and Policy Implications

This study contributes to the existing literature on the empirical analysis of contagion risk by using innovative non-parametric (Kendall and chi-plots) and parametric approaches i.e. Copulas (Clayton, Gumbel and Normal distribution). After employing non-parametric and parametric estimations for determining contagion risk in the Vietnamese banking system, we conclude that spillover effects exist between these banks. There is strong evidence on the sensitivity of the banking sector to suggest contingent effects. From a financial perspective, our investigation leads us to the following important insights:

1. Results suggest that the Gumbel Copulas (with right-tail dependence) are appropriate for pairing, where at least one bank is state-owned. This means that a bank holding public capital in Vietnam will positively influence the other bank because the State Bank of Vietnam plays the roles of governing and lender of the last resort in the financial system. In a realistic sense, the State Bank of Vietnam has intervened in the banking market when it happens to receive a shock from 'noisy' or Pure Contagion.
2. Contagion risk in the banking system emerges when banks are cross-owned, such as Vietnam Commercial Joint Stock Export-Import Bank (EIB), A Chau Bank (ACB) and Joint Stock Commercial Bank for Investment and Development of Vietnam (BID).
3. A commercial bank with state-owned capital may lead to contagion risk if they operate inefficiently or invest in a weak bank. To elaborate, the Vietnam Joint Stock Commercial Bank for Industry and

Trade (CTG) share the probability of loss with National Citizen Commercial Joint Stock Bank (NVB).

4. Some banks with a high ratio of non-performing loans cause contagion risk among banks. For instance, Vietnam Commercial Joint Stock Export-Import Bank (EIB) and Saigon Thuong Tin Commercial Joint Stock Bank (STB), BID, A Chau Bank (ACB) have a left-tail dependence, which represents a contagion risk with a simultaneous loss in the face of a returns shock.

Based on the findings of this study, there are important policy implications for investors, policymakers and board of governors of Vietnamese banks. Regarding investors, they should be careful while diversifying their portfolio and avoid adding high dependence bank stocks in the same portfolio. Our results show that Vietnamese banks have remarkable exposure to each other and hence an adverse shock to a bank can cause severe damage to their counterparts, depending on the degree of exposure in each case. As a result policymakers should know the roles of state-owned capital banks, including the potential that they may act as an important factor in the banking system when markets face shocks. Finally, yet importantly, board management of Vietnamese banks should assess risk more systemically when making investments by cross-owned methods. This may be a good tool to earn profit, but due to spillovers it is also a source of risk. Based on application of method and models, our study can also be extended to other developing but also developed economies. A comparative analysis focused on the stage of economic and financial development may give further insight into the contagion risk in the banking sector by using the subject approaches. However, macro-prudential issues also indicate that many methods and approaches may offer insight[14].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could appear to influence the work reported in this paper.

[14] See e.g. Morgan and Patomäki (2017) and Nasir and Morgan (2018).

References

Aharony, J. & Swary, I. 1983, 'Contagion effects of bank failures: Evidence from capital markets', *Journal of Business*, pp. 305-22.

Aloui, R., Aïssa, M.S.B. & Nguyen, D.K. 2011, 'Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?', *Journal of Banking & Finance*, vol. 35, no. 1, pp. 130-41.

Baur, D.G. 2012, 'Financial contagion and the real economy', *Journal of Banking & Finance*, vol. 36, no. 10, pp. 2680-92.

Bekaert, G., Ehrmann, M., Fratzscher, M. & Mehl, A. 2014, 'The global crisis and equity market contagion', *The Journal of Finance*, vol. 69, no. 6, pp. 2597-649.

Benston, G.J. 1986, *Perspectives on Safe & Sound Banking: Past, Present, and Future*, Cambridge, Mass.: MIT Press.

Bagehot, Walter. 1873. Lombard Street. Homewood, IL: Richard D. Irwin.

Balinder, A. S. (2013), After the Music Stopped: The Financial Crisis, the Response, and the Work Ahead, Penguin, ISBN-10: 1594205302.

Bhatti, M.I. & Nguyen, C.C. 2012, 'Diversification evidence from international equity markets using extreme values and stochastic copulas', *Journal of International Financial Markets, Institutions and Money*, vol. 22, no. 3, pp. 622-46.

Bloomberg (2016), Vietnam's Economy Is an Emerging Market Standout, available at https://www.bloomberg.com/news/articles/2016-01-18/vietnam-growth-makes-it-emerging-market-standout-in-shaky-world accessed on 7th January 2018

BNP Paribas, (2007), BNP Paribas Investment Partners temporaly suspends the calculation of the Net Asset Value of the following funds : Parvest Dynamic ABS, BNP Paribas ABS EURIBOR and BNP Paribas ABS EONIA, Available at https://group.bnpparibas/en/press-release/bnp-paribas-investment-partners-temporaly-suspends-calculation-net-asset-funds-parvest-dynamic-abs-bnp-paribas-abs-euribor-bnp-paribas-abs-eonia accesed on 22nd January 2018.

Borio, C. (2011), "Rediscovering the macroeconomic roots of financial stability policy: journey, challenges and a way forward", Working Paper No. 354, BIS.

Boubaker, A. & Salma, J. 2011, 'Detecting financial markets contagion using copula functions', *International Journal of Management Science and Engineering Management*, vol. 6, no. 6, pp. 443-9.

Cassidy, J. (2008), The Minsky Moment. Subprime mortgage crisis and possible recession, New Yorker, February 4, 2008.

Chen, W., Wei, Y., Lang, Q., Lin, Y. & Liu, M. 2014, 'Financial market volatility and contagion effect: A copula–multifractal volatility approach', *Physica A: Statistical Mechanics and its Applications*, vol. 398, pp. 289-300.

D'Hulster, K. Ötker-Robe,I. (2015), Ring-fencing cross-border banks: An effective supervisory response? Journal of Banking Regulation, Volume 16 (3), pp 169–187.

Diamond, D.W. & Dybvig, P.H. 1983, 'Bank runs, deposit insurance, and liquidity', *Journal of political economy*, vol. 91, no. 3, pp. 401-19.

Dungey, M., Fry, R., González-Hermosillo, B. & Martin, V.L. 2005, 'Empirical modelling of contagion: a review of methodologies', *Quantitative finance*, vol. 5, no. 1, pp. 9-24.

Embrechts, P. 2009, 'Copulas: A personal view', *Journal of Risk and Insurance*, vol. 76, no. 3, pp. 639-50.

Forbes, K.J. & Rigobon, R. 2002, 'No contagion, only interdependence: measuring stock market comovements', *The journal of Finance*, vol. 57, no. 5, pp. 2223-61.

Genest, C. & Favre, A.-C. 2007, 'Everything you always wanted to know about copula modeling but were afraid to ask', *Journal of hydrologic engineering*, vol. 12, no. 4, pp. 347-68.

Grégoire, V., Genest, C. & Gendron, M. 2008, 'Using copulas to model price dependence in energy markets', *Energy risk*, vol. 5, no. 5, pp. 58-64.

Grossman, R.S. 1993, 'The macroeconomic consequences of bank failures under the national banking system', *Explorations in Economic History*, vol. 30, no. 3, pp. 294-320.

Hasan, I. & Dwyer, G.P. 1994, 'Bank runs in the free banking period', *Journal of Money, Credit and Banking*, vol. 26, no. 2, pp. 271-88.

Hui, H.F.X. 2005, 'The Co-movement Between China and USA Stock Markets [J]', *Journal of Finance*, vol. 11, p. 014.

Huynh, T. L. D., Nguyen, S. P., & Duong, D. (2018, January). Contagion Risk Measured by Return Among Cryptocurrencies. In *International Econometric Conference of Vietnam* (pp. 987-998). Springer, Cham.

Huynh, T.L.D (2019). Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student'st Copulas. Journal of Risk and Financial Management, 12(2), 52.

Huynh, Toan Luu Duc & Burggraf, Tobias (2019). If Worst Comes to Worst: Co-Movement of Global Stock Markets in the US-China Trade War. Business and Economics Letters (forthcoming). Available at SSRN: https://ssrn.com/abstract=3466245 or http://dx.doi.org/10.2139/ssrn.3466245

Hwang, E., Min, H.-G., Kim, B.-H. & Kim, H. 2013, 'Determinants of stock market comovements among US and emerging economies during the US financial crisis', *Economic Modelling*, vol. 35, pp. 338-48.

Jin, X. 2017, 'Downside and upside risk spillovers from China to Asian stock markets: A CoVaR-copula approach', *Finance Research Letters*.

Kaufman, G.G. 1994, 'Bank contagion: A review of the theory and evidence', *Journal of Financial Services Research*, vol. 8, no. 2, pp. 123-50.

Kenourgios, D., Samitas, A. & Paltalidis, N. 2011, 'Financial crises and stock market contagion in a multivariate time-varying asymmetric framework', *Journal of International Financial Markets, Institutions and Money*, vol. 21, no. 1, pp. 92-106.

Kindleberger, C. (1978), Manias, Panics and Crashes. New York,Basic Books

Kosmidou, K. Kousenidis, D. Ladas, A. Negkakis, C., 2017. "Determinants of risk in the banking sector during the European Financial Crisis," Journal of Financial Stability, Elsevier, vol. 33(C), pages 285-296.

Levine, R. (2005), “Finance and Growth: Theory and Evidence.” In Handbook of Economic Growth, edited by Philippe Aghion and Steven Durlauf, New York: Elsevier, 865–934.

Lengwiler, Y. Maringer, D. (2015), Regulation and contagion of banks, Journal of Bank Regulation, Volume 16 (1), pages 64–71.

Lim, C. Y. Woods, M. Humphrey, C. Seow, J.L. (2017) The paradoxes of risk management in the banking sector, The British Accounting Review,49 (1) pp. 75-90.

Lütkepohl, H., 1991, Introduction to multiple time series analysis (Springer-Verlag, Berlin).

Lütkepohl, H., Reimers, H. E. (1992). Granger-causality in cointegrated VAR processes The case of the term structure. Economics Letters, 40(3), 263-268.

Mälkönen, V. (2004), Capital adequacy regulation and financial conglomerates, Journal of International Banking Regulations, Volume 6 (1), pp 33–52.

Markose, S.M. (2013), Systemic risk analytics: A data-driven multi-agent financial network (MAFN) approach, Journal of Banking Regulation, Volume 14 (3–4), pp 285–305.

Mesfioui, M. Quessy, J. F. (2008). Dependence structure of conditional Archimedean copulas. Journal of Multivariate Analysis, 99(3), 372-385.

Markowitz, H.M. 1991, 'Foundations of portfolio theory', *The journal of finance*, vol. 46, no. 2, pp. 469-77.

McKinnon, Ronald. 1973. Money and Capital in Economic Development. Washington: The Brookings Institution.

Miller, M.B. 2013, *Mathematics and Statistics for Financial Risk Management*, John Wiley & Sons.

Minsky, H.P. (1974), The Financial Instability Hypothesis, The Jerome Levy Economics Institute of Bard College, Working Paper No. 74.

Morgan, J. Patomäki, H. (2017) 'Contrast explanation in economics: its context, meaning, and potential', Cambridge Journal of Economics 41(5): 1391-1418

Nasir, M. A. Ahmad, M. Ahmad, F. Wu, J.(2015), Financial and Economic Stability as 'Two Sides of a Coin': Non-Crisis Regime Evidence from the UK Based on VECM, Journal of Financial Economic Policy, Vol. 7 Issue: 4, pp. 327-353,

Nasir, M.A. Du, M. J. (2017), Integration of Financial Markets in Post Global Financial Crises and Implications for British Financial Sector: Analysis Based on A Panel VAR Model, Journal of Quantitative Economics pp 1–26.

Nasir, M. A. Morgan, J. (2018) 'The unit root problem: Affinities between ergodicity and stationarity, its practical contradictions for central bank policy, and some consideration of alternatives', Journal of Post Keynesian Economics 41(3): 339-363.

Nelsen, R. B. (2006). An introduction to copulas, ser. *Lecture Notes in Statistics. New York: Springer*.

Nguyen, C., Bhatti, M.I. & Henry, D. 2017, 'Are Vietnam and Chinese stock markets out of the US contagion effect in extreme events?', *Physica A: Statistical Mechanics and its Applications*, vol. 480, pp. 10-21.

Nguyen, G. (2017), Vietnam Stocks Could Hit a 10-Year High in 2017: Analysts, available at [https://www.bloomberg.com/news/articles/2017-01-19/asian-outperformer-vietnam-stocks-seen-reaching-10-year-high] accessed on 19th September 2017.

Ong, L., Mitra, S. & Chan-Lau, J.A. 2007, 'Contagion risk in the international banking system and implications for London as a global financial center'.

Postlewaite, A. & Vives, X. 1987, 'Bank runs as an equilibrium phenomenon', *Journal of political Economy*, vol. 95, no. 3, pp. 485-91.

Reboredo, J.C. 2011, 'How do crude oil prices co-move?: A copula approach', *Energy Economics*, vol. 33, no. 5, pp. 948-55.

Sahay, R. Čihák, M. N'Diaye, P. Barajas, A. Bi, R. Ayala, D. Gao, Y. Kyobe, A. Nguyen, L. Saborowski, C. Svirydzenka, K. Yousefi, S. R. (2015), Rethinking Financial Deepening: Stability and Growth in Emerging Markets, IMF Staff Discussion Note, SDN/15/08

Samarakoon, L.P. 2011, 'Stock market interdependence, contagion, and the US financial crisis: The case of emerging and frontier markets', *Journal of International Financial Markets, Institutions and Money*, vol. 21, no. 5, pp. 724-42.

Saunders, A. 1987, 'The Interbank Market, Contagion Effects and International Financial Crises and Threats to International Financial Stability, edited by R. Portes and AK Swoboda', *New York, NY: Cambridge University Press*, vol. 196, p. 232.

Singh, Dalvinder and LaBrosse, John Raymond, Developing a Framework for Effective Financial Crisis Management (February 9, 2012). Warwick School of Law Research Paper No. 2012/05. Available at SSRN: https://ssrn.com/abstract=2001978 or http://dx.doi.org/10.2139/ssrn.2001978

Sklar, M. (1959). Fonctions de repartition an dimensions et leurs marges. *Publ. inst. statist. univ*. Paris, 8, 229-231.

Schoenmaker, D. 1996, *Contagion risk in banking*, LSE Financial Markets Group, pp. 86-104.

Scott, H.S. 2016, *Connectedness and Contagion: Protecting the Financial System from Panics*, Mit Press.

Shaw, Edward. 1973. Financial Deepening in Economic Development. New York: Oxford University Press.

Sklar, M. 1959, 'Fonctions de repartition an dimensions et leurs marges', *Publ. inst. statist. univ. Paris*, vol. 8, pp. 229-31.

Taylor, P. (2013). Tiberius Used Quantitative Easing To Solve The Financial Crisis Of 33 AD, http://www.businessinsider.com/qe-in-the-financial-crisis-of-33-ad-2013-10?IR=T

Tucker, P. (2009), Paul Tucker: The repertoire of official sector interventions in the financial system – last resort lending, market-making, and capital, available at https://www.bis.org/review/r090608c.pdf.

Ullah, S., Wang, Z., Stokes, P. and Xiao, W., 2019. Risk perceptions and risk management approaches of Chinese overseas investors: An empirical investigation. Research in International Business and Finance, 47, pp.470-486.

Ye, W., Liu, X. & Miao, B. 2012, 'Measuring the subprime crisis contagion: Evidence of change point analysis of copula functions', *European Journal of Operational Research*, vol. 222, no. 1, pp. 96-103.

Zhang, B. & Li, X.-M. 2014, 'Has there been any change in the comovement between the Chinese and US stock markets?', *International Review of Economics & Finance*, vol. 29, pp. 525-36.