Testing Contagion in Asian Nominal Exchange Rates (VARX-EGARCH) using Vine-Copulas

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Dedication

To José Augusto my wonderful **DAD** in heaven, Alicia my lovely **MOM** and Freddy my awesome **BROTHER**.

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Abstract

The evidence of contagion has not been conclusive in the literature, neither it has a unique definition. Nevertheless, Forbes and Rigobon (2001) describes it as a significant increase in cross-market linkages after the occurrence of a shock in a country's financial market. Hence one can distinguish between temporal and permanent mechanisms for crises' transmission. It is also a useful framework for empirically testing contagion in a general set-up. This adaptability is employ on nine Asian Nominal Exchange rates with different arrangements. A VARX-EGARCH is used in order to model each currency's volatility and the feedbacks to news and innovations as proposed by Nelson (1991). This document uses the theorem of Sklar (1959), the automated strategy of Dissmann et al. (2013) and the tail dependence criterion proposed by Cherubini et al. (2004). The analysis yields that the majority of tails are symmetric. The Philippines peso highly co-moves to appreciations and depreciations with other six currencies in the region. And Australian dollar, Japan yen and New Zealand dollar form a block of currencies (interdependence).
Keywords: Financial Crises, Contagion, Foreign Exchange, Econometric Methods, Econometrics, Copulas, R-vine, Tail dependence.

Résumé

Dans la littérature, il ne existe pas une évidence ou une unique définition de contagion. Néanmoins, Forbes and Rigobon (2001) décrivent contagion comme une augmentation significative des liens entre marchés après un shock dans le marché financier du pays et dans ce cas, on peut distinguer entre les mécanismes temporaires et permanents dans la transmission des crises. Aussi, c'est un plan de référence utile pour analyser empiriquement des épisodes de contagion. Cette adaptation est utilisée en neuf types des taux nominaux asiatiques avec des différents modifications. On travaille sur un VARX-EGARCH pour modéliser la volatilité de chaque devise, la rétro-alimentation des nouvelles et des innovations tel comme Nelson (1991) propose. Ce rapport utilise le théorème de Sklar (1959), la stratégie automatisée de Dissmann et al. (2013) et le critère de dépendance des aires postulé par Cherubini et al. (2004). L'analyse montre que la plupart des aires sont symétriques. Le peso philippin réagi à des appréciations et dépréciations des autres six devises différentes de la région. Pour le dollar australien, le yen japonais et le dollar néo-zélandais forment un bloc de devises (interdépendance)
Mots clés: Crise financière, Contagion, Taux de change, Méthodes économétriques, Économétrie, Copules, R-vine, Dépendance des aires.

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List of abbreviations

Abbreviation	Definition
ASEAN	Association of Southeast Asian Nations.
ASEAN plus three	ASEAN and three nations: China, Japan, and South Korea.
AUD/USD	Australian Dollar/US Dollar.
CBOE	Chicago Board Options Exchange.
FED	Federal Reserve System US.
GARCH	Generalized Autoregressive Conditional Heteroscedasticity.
HKD/USD	Hong Kong Dollar/US Dollar.
IMF	International Monetary Fund.
JPY/USD	Japan Yen/US Dollar.
KPSS	Kwiatkowski Phillips Schmidt Shin test.
KRW/USD	South Korea Won/US Dollar.
LM	Lagrange Multiplier.
MYR/USD	Malaysia Ringgit/US Dollar.
NZD/USD	New Zealand Dollar/US Dollar.
PHP/USD	Philippines Peso/US Dollar.
SGD/USD	Singapore Dollar/US Dollar.
S&P500	Standard & Poor's 500 Index.
TWD/USD	Taiwan Dollar/US Dollar.
0	Independence copula.
1	Gaussian copula.
2	Student t copula (t-copula).
3	Clayton copula.
4	Gumbel copula.
5	Frank copula.
6	Joe copula.
7	BB1 copula.
8	BB6 copula.
9	BB7 copula.
10	BB8 copula.
13	Rotated Clayton copula (180 degrees; survival Clayton).
14	Rotated Gumbel copula (180 degrees; survival Gumbel).
16	Rotated Joe copula (180 degrees; survival Joe).

Abbreviation	Definition
17	Rotated BB1 copula (180 degrees; survival BB1).
18	Rotated BB6 copula (180 degrees; survival BB6).
19	Rotated BB7 copula (180 degrees; survival BB7).
20	Rotated BB8 copula (180 degrees; survival BB8).
23	Rotated Clayton copula (90 degrees).
24	Rotated Gumbel copula (90 degrees).
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27	Rotated BB1 copula (90 degrees).
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1. Introduction

A study by Bordo and Murshid (2001) found evidence of periods of crisis for almost every decade since 1825; particularly the Baring Crisis in 1890 and the U.S. banking crisis in 1893. Furthermore, Laeven and Valencia (2008) at the IMF recorded 208 currency crises, 124 banking crisis, and 63 sovereign debt defaults and restructures since 1970. Henceforth there is wealth of literature to learn from as these events have taken a prominent role in economics; mainly through modelling for measuring and understanding their causes and channels of transmission.

Studies of some of the episodes described above produced a number of different models that Claessens et al. (2001) classified into two generations: the first generation is called balance of payments models that focus on a country's weak fundamentals and the second generation or multiple-equilibrium models that includes investors' expectations and government' policy objectives. These authors' concerns with the standard theories for explaining and predicting crises is that they are no longer suitable, which means economic modeling must progress in order to keep up with economic reality.[1]

Additional to these two generations De Gregorio and Valdes (2001), suggested a third generation that included links between financial markets, banking crisis and foreign exchange markets. Therefore, this document considers the progress made and aims at developing new understanding of currency crises.

The correlation coefficient or Pearson correlation was the first and basic indicator used for measuring irregular movements between currencies. Early works such King and Wadhwani (1990); Lee and Kim (1993); Calvo and Reinhart (1996); Frankel and Schmukler (1996) applied this method. In essence, they tested risk contagion by the decline or increase of the coefficients in different periods. Thus, for markets that exhibit a low degree of co-movement during stable periods, a significant increase in movement in the course of a crisis could indicate contagion. In contrast, for markets that already exhibit a high degree of co-movement during stable periods, a high movement at the time of a crisis could mean interdependence.

However, there are numerous drawbacks for linear correlations in the Gaussian context or

[1] Fratzscher (1999) emphasizes this argument when he questions the usefulness of first and second generation in explaining the causes of hererogeneity currency crises in different countries and during various episodes.

dependency structures calculated in traditional methods that assume normal distribution. First, linear correlations do not change over time. Second, when there are asymmetric dependencies, linear correlation can not capture such responses and; third, linear correlation is unable to pick up extreme downside risk spillovers. Moreover, Valdés (1997); Arias et al. (1998); Baig and Goldfajn (1999) argue that correlation estimation must control for economic shifts, changes in commodity prices and/or fundamentals, risk perception or preferences to identify pure contagion. Marçal et al. (2011) dismissed the correlation argument completely when disputing that contagion can not be seen as episodes of high correlation. Instead contagion should be observed as a structural or instability shift that occur during a crisis.

These critiques can be analysed by a far more superior method called copula. Copulas solve many of the issues with linear correlations and provide the means to create a multivariate distribution with a range of types of dependence. This document applies one of the several measures proposed by Cherubini et al. (2004) to identify contagion; the tail dependence. This method is performed in three steps; first, the marginal distribution is modelled on each series; second, the R-vine copula is estimated using the transform to the uniform distribution associated with the standardized residuals of the model in step one and finally the tail dependence is calculated.

This path to identify contagion that implies the use of copulas and the tail dependence should be preferable to just modelling the first moment using a structure that is appropriate in statistics and economics. The model can illustrate lineal relations between different variables when the relevant tests are enforced. Whereas the copula approach can capture no-linear dependences. Fortunately this document includes both methods, the model and the copulas. In any case an information criteria can determine which method is most appropriate.

1.1. What is Contagion?

Certainly there is no consensus among economists on what contagion might be. The complexity embedded in contagious contexts makes it difficult to identify and isolate the contagion *per se*. However, there are a few academic definitions used depending on the object of the analysis (stock market crisis, currency crisis, banking crisis, et.c). Rigobon (2002) classified them into two categories:

The first relates to contagion as a change in the propagation mechanism around the crisis. That is an increase in the strength of how shocks are transmitted across countries (shift contagion) and, the second that centres on the type of propagation mechanism driving the transmission i.e. the proportion of shock that is not transmitted through the 'standard' channels (pure contagion).

Pericoli and Sbracia (2003) reviewed five definitions of contagion:

(i.) Contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country.

(ii.) Contagion occurs when volatility of asset prices spills over from the crisis country to other countries.

(iii.) Contagion occurs when cross-country co-movements of asset prices can not be explained by fundamentals.[2]

(iv.) Contagion is a significant increase in co-movements of prices and quantities across markets, conditional on a crisis occurring in one market or group of markets.

(v.) (Shift-)contagion occurs when the transmission channel intensifies or, more generally, changes after a shock in one market. Forbes and Rigobon (2001) defined this contagion as a significant increase in cross-market linkages after a shock to an individual country (or group of countries). They proposed the term 'shift-contagion' instead of 'contagion'. They explained that shift contagion is sensible because it is not only clarifies that contagion arises from a shift in cross-market linkages, but it also avoids taking a stance on how the shifts occurs.[3]

This document aims to utilise more than one definition, an approach not yet used by previous works. The pure contagion definition of Rigobon (2002) is central for this document specifically for the econometric part. In addition definition (i.) is refer to in the copula analysis; as by definition tail dependence is a conditional probability. That is, when the limiting proportion that one margin exceeds a certain threshold given that the other margin has already exceeded that threshold.

1.2. Why this region?

The analytical focal point is a particular region, in this case a set of nominal exchange rates in Asia. To justify this 'focus' on a region the contributions of Glick and Rose (1999); De Gregorio and Valdes (2001); Beirne and Gieck (2014) are very helpful when they stated

[2]This definition is somehow difficult to adopt considering two aspects: (a) the broad meaning of fundamentals and (b) the choice of the fundamentals. However, Chu et al. (2000) uses a group of fundamentals to demonstrate contagion and their impact in the exchange-rate returns. He concluded that although the macroeconomic variables used cannot explain the short run exchange rate dynamics, currency traders paid more attention to changes in macroeconomic conditions.

[3]These authors concluded that if the statistical measure of correlation coefficients was adjusted for heteroskedasticity, there was virtually no contagion only interdependence during the East Asian crisis, Mexican peso collapse, and U.S stock market crash.

that contagion is strongly and almost exclusively, driven by neighbourhood effects and that geographic proximity is the prime candidate for currency crises and contagion.

'Proximity' to the country where the crisis originated was also used by Fratzscher (1999) but in a different way. He divided 'proximity' into real and financial integration. Therefore, studying this region is compelling due to important integrations mainly driven by markets and foreign direct investment (FDI). As Kawai (2005) puts it, the expansion of foreign trade, direct investment and financial flows has created a 'naturally' integrated economic zone. A number of studies have recognized the importance of this region's long term economic relationships such as Kohli et al. (2011); ADBI. (2016).

Moreover, macroeconomic interdependence within the region is becoming stronger. Comovements in the downside in 1998 and upside in 1999-2000 are pertinent indicators. Furthermore, GDP growth rates, real private consumption, real fixed investment and inflation indicate macro-similarities that increase countries' vulnerability to volatility. Hence, countries become more vulnerable to the risk of contagion from negative shocks by neighbours. [4]

There has been significant progress in financial integration by shrinking controls on the financial system, more access to financial services in foreign institutions and liberalization of the capital account. Commercial bank loans and portfolio allocation had certainly connected the economies in the region, establishing positive correlations of asset price movements in the region. Thus, Kawai (2005) interpreted that part of the contagion of currency crises in 1997 was due to these financial linkages.

1.3. What is the purpose and method?

The purpose of this document is to test contagion between nine Asian nominal exchange rates (regardless of their arrangements) for the synchronized period of Dec. 1996 to Mar. 2017 using copulas and tail dependences. As mentioned above two definitions of contagion are appropriate following the stage of the work done and the results found in order to determine contagion. This document is divided in five chapters. The second chapter analyses the data and reviews the appropriateness of the model with regards to different econometric techniques and the economic theory. In chapter three some preliminary test are consider, the order (p,s) and the VARX-EGARCH are estimated. Chapter four introduces the basics of Copulas following the pionering work of Sklar (1959), the extended work of R-Vine is

[4] In the Asian crisis 1997-1998; GDP growth sharply declined in the economies affected from 7.1 percent pre-crisis average to -7.6 percent in 1998. Kawai (2010) acknowledged that Indonesia had the largest GDP contraction by more than 13% in 1998. The simultaneity of the economic contraction in this region affected economies in 1998 reflected strong regional economic interdependence.

succinctly explained thenceforth it is applied to the data concerning this document and the tail dependences. The last chapter concludes.

2. Data and Econometrics

This document covers a synchronized period from 10/Dec/1996 to 15/Mar/2017 for daily closing values obtained primarily from Bloomberg L.P. and some Reserve Banks.[5] The data is adopted according to availability in nominal exchange rates, interest rates [6] and stock market values for nine Asian economies: Australia, Hong Kong, Japan, Malaysia, New Zealand, Singapore, South Korea, Taiwan and The Philippines. I focus on these countries for feasibility in data collection.

Furthermore, these economies have different foreign exchange arrangements (see table 2.1). The IMF classifies them by *de facto* arrangements, which may differ from their officially announced, *de jure* arrangements. There are four major categories: hard pegs (such as exchange arrangements with no separate legal tender and currency board arrangements); soft pegs (including conventional pegged arrangements, pegged exchange rates within horizontal bands, crawling pegs, stabilized arrangements, and crawl-like arrangements); floating regimes (such as floating and free floating); and a residual category of other arrangements.

These important characteristics are visualised in figure A.2 and complemented by the following:

(i.) Hong Kong has maintained a linked exchange rate system with the U.S. dollar since 1983. Hong Kong Monetary Authority (HKMA) intervenes to keep the rate between 0.1273 and 0.1290 as seen in figure A.2. Hong Kong's three designated currency issuing banks: The Bank of China, HSBC and Standard Chartered Bank must deposit with the HKMA sufficient U.S. dollar denominated reserves to cover their issuance of Hong Kong dollars.

(ii.) Malaysia adopted selective exchange controls in 1998 and fixed their currency to the U.S. dollar to the value of 0.2631. In 2005 the arrangement changed to a managed

[5] Although the study focus on a region there are empirical difficulties when using the closing times. There are differences in time zone that affect the transmission mechanism. In particular; Thailand's market closes at 5pm local time, no other market closes at exactly the same point in time: five hours for Taiwan, four hours for Japan, Korea and the Philippines, three or four hours for Australia and one for Malaysia and Singapore. This can partially be solve methodologically by using lags in the data. Kleimeier et al. (2008) concluded that if the transmission of shocks is immediate and exactly *time-aligned* as the authors called it, correlations reveal the true nature of crises and there is more evidence for contagion.

[6] Overnight interest rates are use as suggested by Bernanke (1990); Christiano et al. (1994).

Table 2.1.: Foreign Exchange Arrangements.

Country	**Exchange rate arrangement**	**Monetary policy framework**
Australia.	Free floating.	Inflation-targeting.
Hong Kong.	Currency board.	U.S. dollar anchor.
Japan.	Free floating.	Inflation-targeting.
Malaysia.	Other managed arrangement.	Other.[1]
New Zealand.	Floating.	Inflation-targeting.
Singapore.	Stabilized arrangement.	Composite.
South Korea.	Floating.	Inflation-targeting.
Taiwan.[2]	Other managed arrangement.	Inflation-targeting.
The Philippines.	Floating.	Inflation-targeting.

Source: IMF, Table 2 as published in Monetary and Department (2016).
[1] Includes countries that have no explicitly stated nominal anchor, but rather monitor various indicators in conducting monetary policy.
[2] No reference for this country in the IMF report. Author's classification.

float as depicted in A.2.

(iii.) The New Zealand dollar has mostly been allowed to freely float since 1985, with only rare and modest intervention from the Reserve Bank of New Zealand since 2007.

(iv.) The official exchange rate policy in South Korea has been a free floating system since 1997. However, in 2008 the South Korea government sold about $1 billion for won to stop a disorderly decline in the value of Korea's currency.[7]

(v.) The Philippines implemented a flexible exchange rate system in 1973 and reserved the right to intervene. In 1992 the Central Bank decided to liberalize nearly all capital flows and foreign exchange transactions.

(vi.) Following the establishment of the Taipei Foreign Exchange Market in 1979, a flexible exchange rate system was formally implemented in Taiwan.

(vii.) Since 1981, Singapore policy has been centred on a managed exchange rate. It incorporates key features of the basket, band and crawl regimes.[8]

[7] For more details refer to the article by Choonsik and Jong-woo (2008) in Reuters.
[8] Furthermore, the Congressional Research Service in the U.S. published a report by Martin (2017). It claimed that from 2011 to 2013, Malaysia, Singapore, Thailand and the Philippines appeared to have adopted exchange rates regimes to keep their currencies relatively stable with respect to China's Renminbi. The Congressional Research Service called this behaviour a 'Renminbi Bloc'. It illustrated that

(viii.) Japan has enforced a floating exchange rate since 1973 and monetary authorities have not intervened since 2004. Australia began a floated regimen in 1983.

Some other important characteristics of interest rates and stock market data must be highlighted:

(a.) Singapore's interbank overnight rate and Singapore Government Securities overnight repo rate were discontinued on 1/Jan/2014. After reviewing the demand and usage of these the Monetary Authority of Singapore (MAS) administered financial benchmarks. Then, in order to obtain contemporary data; the Singapore Overnight Rate Average (SORA), which is the weighted average rate of all overnight cash transactions brokered in Singapore between 9am and 6.15pm, was used to complete the data.

(b.) The Singapore Stock Market was recalculated twice in 1998 and 2008 according to the FTSE methodology. Then the oldest index was extended up-to-date by using the new index as a reference.

(c.) The Hong Kong Interbank Offered Rates (HIBOR) are the middle closing rates quoted by the Standard Chartered Bank in the interbank money market. However, the HIBOR was discontinued on 1/Jan/2013. To extend this rate the Hong Kong Association of Bank (HKAB) was used. The HKAB is the source and owner of the Hong Kong Interest Settlement Rates (HKD). The daily HKD are fixed by reference to market rates for HKD deposits in Hong Kong interbank markets and;

(d.) Interbank Interest rates for Australia and New Zealand were gathered directly from their Reserve Banks and for the other countries Bloomberg's similar rates were used.

2.1. Statistics and tests

Table B.6 presents the main statistics for nominal exchange rates. Skewness as a measure of the asymmetry of the probability distribution about the mean is negative only for Hong Kong and New Zealand, indicating that the tail on the left side of the probability is longer than the right side. When the distribution is negatively skewed, the standard deviation will underestimate risk. The opposite occurs for the majority of countries that have positive values. Standard deviation in episodes of devaluation can overestimate risk. Therefore, it is interesting to observe positive (negative) skewness as shocks can affect the returns in terms of devaluations (appreciations) for every country's currency and its effects on volatility in both cases.

the bloc may have emerged because those nations' economic and trade ties with China. As China was actively promoting the use of its currency for trade settlements in Asia.

Kurtosis is a measure of the degree of fat tails. High kurtosis generally means that more of the variance is due to infrequent extreme deviations than predicted by the normal distribution, and is a strong, but not perfect, signal that a return series has fat tails. Excess kurtosis is defined as kurtosis over and above three. For all cases the values are different from three (see table B.6). Moreover; Japan and South Korea have values close to three. That could indicate normal distributions. Malaysia has a value of 4.50 and the Philippines is 14.22 in these cases the distribution is leptokurtic and has more extreme values relatively to the Gaussian distribution law.

On the other hand; Australia, Hong Kong, New Zealand, Singapore and Taiwan have values less than three. In these cases the distributions are platykurtic and have fewer extreme values than the Gaussian distribution. In these cases it seems that appreciations or devaluations in extreme episodes are not present for these economies. This feature encourages the study of the dynamics between these currencies.

The probability for Jarque-Bera statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. In all countries give evidence for rejecting the normal distribution hypothesis at any confidence level. These results indicate that the distribution of residuals in the model should allow different distributions from the normal distribution as described below.

The Kolmogorov-Smirnov statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution; in this case a normal distribution. It has the advantage of making no assumptions about the data distribution except the continuity of both distribution functions.

The test statistic is the maximum difference in value of $D = max[F_x(u) - F_y(u)]$, where $F_x(u)$ is the empirical distribution and $F_y(u)$ is the normal distribution. Therefore the null hypothesis is that the true distribution function of x is equal to the hypothesized distribution function ($D = 0$) and the alternative hypothesis being two-sided. From table B.6 every value is $D > 0$. Indicating that the data is not normally distributed.

2.2. Econometric background

Different econometric techniques have been used to test contagion. Videlicet: simple cross-market correlation coefficients King and Wadhwani (1990); [9] co-integration techniques Longin and Solnik (1995); probit and logit models Eichengreen et al. (1996); Glick and Rose

[9] Forbes and Rigobon (2001) asserted that testing contagion based on correlation coefficients is biased and inaccurate due to heteroskedasticity. They proposed calculating the correlation using an unconditional

(1999); Salgado et al. (2000); Van Rijckeghem and Weder (2001) and vanilla GARCH model Engle III et al. (1988); Hamao et al. (1990); Edwards et al. (1998).

Most academic studies on conditional variance used vanilla models. This document aims at a more complex structure not applied in this field of academic research. An Exponential GARCH (EGARCH) carried out by Nelson (1991) for conditional variance using a VARX(p,s) structure as the mean equation. The VARX(p,s) should give the nominal exchange rate in the short run, this framework is subsequently used as an input for the conditional exponential variance.

There are various advantages of VAR(p) modelling: There is no need to specify which variables are endogenous or exogenous, all variables are treated as endogenous. AR(p) models can be viewed as a restricted case of VAR(p) models. They can offer a rich structure, implying that they may be able to capture more features of the data. The X part of the VAR(p) allows other variables that can affect the dependent variable. The main drawback of VARs is the a-theoretical nature and the limited use of economic theory within the model. Therefore, it is convenient to illustrate economic arguments for exchange rate construction applying interest rates and stock markets indexes as exogenous variables as used in this document.

2.2.1. Economic theory

A handy approach to the exchange rates' formation is its value (asset measure). Currencies are assets and their price are the spot exchange rate, the price of one unit of foreign exchange. It is assumed that the price of goods are sticky. The uncovered interest parity (UIP) is fundamental for the asset approach to exchange rates. A significant characteristic of the UIP is international capital mobility, this may be desired as a means to promote integration, efficiency and risk sharing.

In the UIP the interest rate on dollar deposits must equal the interest rate on an Asian country's deposits plus the expected rate of depreciation of the dollar. Or Dollar rate of return on dollar deposits is equal to the expected dollar rate of return on an Asian country's deposits. $E_{Asia/\$} = E^e_{Asia/\$}\frac{1+i_{Asia}}{1+i_\$}$ [10], the nominal interest rate and the expected future exchange rate[11] are treated as known exogenoues variables.

correlation coefficient

$$\rho = \frac{\rho^*}{\sqrt{1+\delta[1-(\rho^*)^2]}}$$

where ρ^* is the conditional correlation coefficient, ρ is the unconditional correlation coefficient, and δ is the relative increase in the variance of x.

[10] The subscript Asia referes to any single country in the Asia region.

[11] If covered interest parity and uncovered interest parity hold; the forward rate must equal the expected

If interest rates are to explain exchange rates in the short run but a key determinant of the exchange rate is the differential in inflation in the long run then the link between the short and long run is the Fisher effect. That is; *ceteris paribus*, a rise in the expected inflation rate in a country will lead to an equal rise in its nominal interest rate. Therefore using the interest rates as instruments for inflation seems adequate in the exogenous structure of the VARX(p,s).

Now turning to the stock market variables, these assets in an economic sense are the means by which individuals hold their claims on real assets. While real assets generate net income to the economy, financial assets simply define the allocation of income or wealth among investors. Investors' returns on securities ultimately come from the income produced by the real assets that were financed by the issuance of those securities.

Thus the success or failure of financial assets depends on the performance of the underlying real assets. For instance GDP gap fluctuations can vary investors' appetite; the inflow of foreign capital and trade balance in turn modifing the demand for real money balances in the short run and changing the exchange rate value. Hence using the stock indexes as instruments for real assets seems suitable in determining the exchange rate.

2.2.2. Asymmetric response

As mentioned this document uses an EGARCH, owing to the arguments put foward by Black (1976). He stressed that stock returns are negatively correlated with changes in returns volatility. In other words, volatility tends to increase in response to 'bad news' hence the return is lower than expected and vice versa; higher than expected returns result from low volatility in response to 'good news'.

Engle and Ng (1993) corroborated Black (1976) by stating that EGARCH differs from the standard GARCH in two respects: (a.) EGARCH allows good and bad news to have different impacts on volatility, while standard GARCH does not, and (b.) EGARCH model allows big news to have a greater impact on volatility than the standard GARCH model. Nelson (1991) then suggested that a model in which the variance responds asymmetrically might be preferable.[12]

The specification for the conditional variance under EGARCH is:

future spot rate $E^e_{Asia/\$}$

[12] Other drawbacks that the author mentioned are the non-negativity constrains and the interpretation of the 'persistence' of shocks to conditional variance.

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{s} \alpha_i \frac{|a_{t-i}| + \gamma_i a_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{m} \beta_j \ln(\sigma_{t-j}^2). \tag{2.1}$$

A positive a_{t-i} contributes $\alpha_i(1+\gamma_i)|\epsilon_{t-i}|$ to the log volatility, whereas a negative a_{t-i} contributes $\alpha_i(1-\gamma_i)|\epsilon_{t-i}|$, where $\epsilon_{t-i} = a_{t-i}/\sigma_{t-i}$. The γ_i parameter thus signifies the leverage effect of a_{t-i}.

The residuals are non-independent of the conditional information and generally non-normal. Hence, it can not be assumed that the only features of conditioning are the mean and the variance. Thus, the conditional distribution of the error term ϵ can be represented as Nelson (1991) suggested. A Generalized Error Distribution (GED):

$$f(z) = \frac{v \cdot \exp\left[-\left(\frac{1}{2}\right)|z/\lambda|^v\right]}{\lambda 2^{(1+1/v)}\Gamma(1/v)}, \quad -\infty < z < \infty, \quad 0 < v \leqslant \infty, \tag{2.2}$$

where $\Gamma(\cdot)$ is the gamma function, and

$$\lambda \equiv \left[2^{(-2/v)}\Gamma(1/v)/\Gamma(3/v)\right]^{1/2}. \tag{2.3}$$

v is a tail-thickness parameter. When $v = 2$, z has a standard normal distribution. For $v < 2$, the distribution of z has thicker tails than the normal and for $v > 2$, the distribution of z has thinner tails than the normal. Thus, the pick of the GED operates well given the nature of the data as formulated by the skewness and kurtosis. The density is normalized to have a mean of zero and a variance of one. However, parameters of the error distributions are assumed to be constant over time.

3. Model performance

This document focuses on contagion through co-movements in detrended exchange rate. Therefore, the daily nominal exchange rate of each country is transformed to represent a ln difference; in other words its expected rate of depreciation. $Y_{t,i}$ is the nominal exchange rate in period t for $t = 1, 2, \ldots, T$ of country i for $i = 1, 2, \ldots, m$:

$$r_{i,t} = ln(Y_{i,t}) - ln(Y_{i,t-1}). \tag{3.1}$$

The continuously compounded returns $r_{i,t}$ is then constructed in a framework that includes a comprehensive group of variables that can describe it for which daily frequency is available. Hence the proposed VARX(p,s):

$$r_{i,t} = \mu + \Lambda(L)r_{i,t} + \Theta(L)X_{i,t} + \epsilon_t. \tag{3.2}$$

where μ is a m-vector, Λ are the usual VAR p coefficient matrices m x m, and Θ are m x d coefficient matrices of exogenous variables or leading indicators.

In equation 3.2 $\Lambda(L) = \Lambda_1 L + \cdots + \Lambda_p L^p$ and $\Theta(L) = \Theta_0 L + \cdots + \Theta_q L^q$, both matrices of polynomials in the lag operator L. $X_{i,t}$ is a set d of idiosyncratic and U.S data. The former contains variables such as: an integrated process I(1) interest rate differential or spread and the return on the local stock market. The latter has the return on the S&P500 and the return on the CBOE volatility index (VIX).[13] And ϵ_t is the residual from the mean equation (the ARCH term).

3.1. Preliminaries

Some statistical tests were carried out for the expected rate of depreciation, interest rate differential and return on the local stock market. Firstly, the Ljung-Box test (1978) is used to check if there exists an autocorrelation within the time series up to a certain number of lags. The statistic used is:

[13] The VIX of CBOE is an implied volatility. This implied volatility is derived under the assumption that the price of the underlying asset follows a geometric Brownian motion.

$$Q = n(n+2)\sum_{j=1}^{h}\hat{\rho}(j)^2/(n-j). \tag{3.3}$$

with n the number of observations and $\hat{\rho}(j)$ the autocorrelation coefficient in the sample when the lag is j up to order h (all estimates are at 5% confidence).

In tables B.1, B.2 and B.3 the test is calculated with a rule of thumb of 20 lags, for which the χ^2 critical values is 31.4104. In every case the null hypothesis is rejected. The data is not independently distributed.

Secondly, the Augmented Dickey-Fuller test is used with 20 lags. It evaluates whether a series contains a unit root, based on a regression of the change in that variable on the lag of the level of that variable:

$$y_t = c + \delta t + \phi y_{t-1} + \beta_1 \triangle y_{t-1} + \cdots + \beta_p \triangle y_{t-20} + \epsilon_t, \tag{3.4}$$

The null hypothesis that there is a unit root can be rejected (see tables B.1 to B.3) at 5% or 1% level; critical values without trend are -2.86 and -3.43 appropriately.

And thirdly, the KPSS test for which the null hypothesis is that a series is stationary was carried out. The test is a one-sided LM statistics. All (except the Philippines in table B.1) of the KPSS levels were not greater than the critical value of 0.463 at 5%, then the alternative hypothesis is rejected in favour of the null. Nonetheless, when evaluating the Philippines at 1% the null hypothesis is not rejected.

3.1.1. Granger Causality

Idiosyncratic exogenous variables could cause exchange rate behaviour in each economy (as elucidated in the section of economic theory). Explanatory variables in equation 3.2 are assessed using Granger (1969) test as in table 3.1. The null hypothesis states that in each case (interest rate differential or return on the local stock market) no causality could reveal exchange rate movements. From the table the null hypothesis can not be rejected for Hong Kong's interest rate and stock market.

This result highlights Hong Kong distinctive exchange rate regimen that affected causality in equation 3.2. There is a commitment from the HKMA to allow the money supply to adjust to whatever level will ensure that the equilibrium exchange rate in the market for foreign currency exchange equals the announced exchange rate. By agreeing to a fixed exchange rate, Hong Kong is abandoning an autonomous monetary policy and therefore interest rate.

Table 3.1.: Granger Causality test

Country \ Granger test	Diff. Spread Interest rate		Ln Diff. Stock Market Index	
	F.Statistic	p-value	F.Statistic	p-value
Australia.	3.28651	1.e-07***	3.14214	4.e-07***
Hong Kong.	1.00114	0.4606	1.27398	0.1679
Japan.	2.76718	9.e-06***	1.13680	0.2927
Malaysia.	10.0985	4.e-36***	12.4050	4.e-46***
New Zealand.	2.26017	0.0004***	1.74734	0.0137**
Singapore.	7.05407	6.e-23***	6.96911	1.e-22***
South Korea.	5.98766	2.e-18***	1.65770	0.0233**
Taiwan.	15.2409	2.e-58***	2.56900	4.e-05***
The Philippines.	98.3923	0.000***	5.72144	2.e-17***

*** Null hypothesis rejected at 1%.
** Null hypothesis rejected at 5%.
Note: In this table the frequency of the data is a moving average of 20 values. Lags in the test are 24. Two-way causation is frequently the case and the opposite direction are presented in table B.4.

Stock markets have no causality on an arbitrary fix exchange rate.

3.1.2. Johansen Cointegration

The macroeconomic time series employed so far are not stationary in their levels but stationary in differences (see tables B.1 to B.3). Hence regressing a non-stationary time series variable on another non-stationary time series variable yields often spurious results and there is no meaningful relationship between them. Therefore, to avoid this issue difference-stationary variables are used in this document.

While this approach is statistically valid, it does have the problem that pure first difference models might have no long-run solution. In macroeconomic theory there should be a stable long-run equilibrium among the exchange rates. Thus, it is important to check for cointegration. In other words, find some long-run relations tying the individual variables together. This is done by the the linear combination of the individual variables which should result in a stationary process; even though individually they are not stationary.

Table 3.2.: Johansen test

	$\boldsymbol{\lambda_{max}}$		$\boldsymbol{\lambda_{trace}}$	
	Test	Critical value	Test	Critical Value
$r <= 8$	2.12	12.25	2.12	12.25
$r <= 7$	9.50	18.96	11.62	25.32
$r <= 6$	14.65	25.54	26.27	42.44
$r <= 5$	21.81	31.46	48.08	62.99
$r <= 4$	27.74	37.52	75.82	87.31
$r <= 3$	34.86	43.97	110.68	114.90
$r <= 2$	47.41	49.42	158.09	146.76^{**}
$r <= 1$	64.34	55.50^{**}	222.43	182.82^{**}
$r = 0$	98.52	61.29^{**}	320.95	222.21^{**}

** Null hypothesis rejected at 5%.

The Johansen (1991) maximum likelihood estimators test is applied based on a VAR(p). There are two test statistic approach:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} ln(1 - \hat{\lambda}_i) \tag{3.5}$$

and

$$\lambda_{max}(r, r+1) = -Tln(1 - \hat{\lambda}_{r+1}) \tag{3.6}$$

where r is the number of cointegrating vectors under the null hypothesis and $\hat{\lambda}_i$ is the estimated value for the ith ordered Eigenvalue from the $\prod$ matrix. 3.5 is a joint test where the null is that the number of cointegrating vectors is less than or equal to r against an unspecified or general alternative that there are more than r. 3.6 is a separate test on each Eigenvalue, and has as its null hypothesis that the number of cointegrating vectors is r against an alternative of $r + 1$.

In table 3.2 the Johansen procedure was calculated for the exchange rates in levels using both 3.5 and 3.6 with a linear trend in cointegration and 20 lags. In the former and later the null hypothesis is rejected up to $r <= 1$ and up to $r <= 2$ respectively. Cointegration vectors exits among the exchange rate that are linear transformations of them. This result validates the model suggested in equation 3.2.

3.2. Order (p,s)

The order of equation 3.2 is estimated following the information criteria:

$$AIC(n) = ln \det\left(\widetilde{\sum}_u(n)\right) + \frac{2}{T}nK^2, \tag{3.7}$$

$$BIC(n) = ln \det\left(\widetilde{\sum}_u(n)\right) + \frac{ln(T)}{T}nK^2, \tag{3.8}$$

$$HQ(n) = ln \det\left(\widetilde{\sum}_u(n)\right) + \frac{2ln(ln(T))}{T}nK^2. \tag{3.9}$$

with $\widetilde{\sum}_u(n) = T^{-1}\sum_{t=1}^{T}\hat{u}_t\hat{u}_t'$ and K the number of parameters estimated.

The selected order for endogenous variables gives the following results: $AIC = 2$, $BIC = 0$ and $HQ = 1$. The exogenous variables provides: $AIC = 20$, $BIC = 20$ and $HQ = 20$.[14] AIC, BIC and HQ criteria select *(p,s)* as (2,20), (0,20) and (1,20) respectively. In table 3.3 AIC and BIC criteria are reported for some VARX(*p,s*) in order to select the appropriate structure. The VARX(2,20) model is selected.

3.2.1. ARCH effects

The squared residuals Ljung-Box statistics are presented in table 3.4. This test uses the following null hypothesis: There is no autocorrelation in the squared residuals up to lag 20. The statistics suggest the presence of autoregressive conditional heteroskedasticity at any confidence level for all countries except Japan. This indicates that using a GARCH model is appropriate.

A multivariate Ljung-Box statistics of the residuals series is given in figure A.1 using table B.5. The structure chosen thus provides a decent approximation to the underlying process of the data. Furthermore, the residuals for this process are presented for weakly stationary series that are not serially correlated using the ACF (see figure A.6).

To recap on the findings: The series are uncorrelated but can still be serially dependent due to a dynamic conditional variance process. When there is evidence of conditional heteroskedasticity or autocorrelation in the squared series, then it has autoregressive conditional heteroskedastic (ARCH) effects.

[14] Here maximum lags of exogenous variables were provided up to a value of 20. Two more maximum lags were calculated e.g. 30 and 50; still resulted with those same extended lags values for the two information criteria. Therefore, 20 was adopt which spans to a month working days.

Table 3.3.: Information criteria to select orders p and s.

VARX(p,s)†	AIC	BIC
(0,20)	-99.104	-90.779
(1,20)	-99.215	-90.712
(2,20)	-99.236	-90.556
(0,30)	-98.943	-86.625
(2,30)	-99.093	-86.418
(0,50)	-98.861	-78.483
(2,50)	-99.014	-78.276

† Two more maximum lags were considered at 30 and 50 both with AR(p) of 0 and 2. In every case VARX(p,s) which includes a p order of 2 could be chosen against their counterpart.

Table 3.4.: Ljung-Box Test for Squared Residuals.

Country	Ljung-Box χ^2
Australia.	248.0491
Hong Kong.	215.105
Japan.	27.46716**
Malaysia.	642.825
New Zealand.	67.42308
Singapore.	270.1176
South Korea.	589.768
Taiwan	163.6102
The Philippines	276.2042

** Null hypothesis not rejected at 5%.

3.2.2. Asymmetries on volatility

Following these findings conditional variance under equation 2.1 and density for innovations equation 2.2 are implemented for every currency in table B.7 with robust standard errors based on White (1982) which produces asymptotically valid confidence intervals. A central outcome is that the GARCH term is significant for all countries at 1%. Whereas the ARCH terms are not significant for every country aside from Japan at 5% and Hong Kong at 10% confidences. The asymmetry term is exclusively not significant for Taiwan. South Korea recorded significance at 5%; the remaining detailed at 1%.

In addition tests for linear ARCH/GARCH against asymmetry by Engle and Ng (1993) under auxiliary regressions are presented. The Sign Bias test examines the impact of positive and negative shocks on the conditional variance not predicted by the model under consideration. The authors considered a dummy variable S^-_{t-1} that takes the value of one when $\epsilon_{t-1} < 0$ and zero otherwise. If the dummy can predict the squared normalized residuals, then the variance model is misspecified.

The Negative Size Bias test utilizes the variable $S^-_{t-1}\epsilon_{t-1}$. It focuses on the different effects that large and small negative shocks have on volatility. And the Positive Size Bias test uses $S^+_{t-1}\epsilon_{t-1}$ or $1 - S^-_{t-1}$ that focuses on the different impacts that large and small positive shocks may have on volatility not explained by the volatility model. These tests use a t-statistic,

contrary to the Join Effect for adding the three variables that is the LM test.[15]

From the results in the table B.7; it appears that the volatility model is not misspecified for The Sign Bias when adopting critical values at any confidence in t-statistic. The Negative Size Bias, Positive Size Bias and Joint Effect are significant simultaneously at 1% for Malaysia, Taiwan and the Philippines only. Australia presents significance in Positive Size Bias at 5% and Joint Effect at 10%.

Moreover, figures A.7 to A.9 present the empirical density of the standardized residual (top). QQ Plot (middle), if the normal assumption is correct, the Gaussian QQ plot should be approximately linear. Consequently, the squared correlation of the points $(m_i, Y_{(i)})$, $i = 1, \ldots, n$, should be near 1. Also the news impact curve (bottom) for each country. The curve plots the next period's volatility (σ^2) that would arise from various positive and negative values of ϵ_{t-1}. It captures the asymmetry in the effect of appreciation or devaluation on volatility (for more details see Engle and Ng (1993)). In this case a positive value of ϵ_{t-1} means that the next period's volatility will depreciate local currency and the opposite occurs for negative ϵ_{t-1}. In addition the news impact curve is more intense for some currencies than others; as curves are polynomial function analogous to straight lines, volatility is more intense as compared to curves that are parabolic (smooth response).

[15]The test is often computed as: $\xi_{LM} = T \cdot R^2$, where R^2 is the squared multiple correlation and T is the number of observations. The LM test follows a χ^2 with three degrees of freedom.

4. Copulas

Copulas are an interesting tool in modelling multivariate dependence given the marginal distributions; particularly when the normality assumption among variables is in question. Moreover, Copulas facilitate isolating dependence between random variables from their marginal distributions. Since the probability integral transform is invertible, the copula also describes the dependence between the original variables. Notably in economics there is often more information about marginal distributions of related variables than their joint distribution. Inasmuch as copulas can capture dependence structure regardless of the form of the margins, a copula approach is likely very useful in econometrics.

The main classes of copulas are elliptical and Archimedean copulas. Elliptical copulas are very popular in finance and risk management because of their easy implementation. Among them exist two copulas, the Gaussian and the Student-t. On the other hand, Archimedean copulas find a wide range of applications for a number of reasons: (a.) They are easy to construct; (b.) The great variety of families; and (c.) The nice properties of its members.

In order to get a grasp of the concept of copulas this section adopts some concepts and notations used by Nelsen (2007). Succinctly, let an n-dimensional distribution function H be decomposed into two parts, the marginal distribution functions F_i and the copula C. H is a functions such that:

(1.) H is n-increasing,

(2.) $H(t) = 0$ for all $\mathbf{t}$ in $\bar{R}^n$ such that $t_k = -\infty$, for at least one k, and $H(\infty, \ldots, \infty) = 0$.

The copula can be used to provide multivariate dependence structure separately from the marginal distribution. Let H be a joint distribution function with margins F_i. Then there exists a copula C such that for all x_i in $\bar{R}^n$ following the seminal work of Sklar (1959),

$$H(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n)). \tag{4.1}$$

Let $F_1, \ldots, F_n$ be the distribution functions. If F_1,...,F_n are all continuous, then C is unique; otherwise, C is uniquely determined on Ran$F_1 \times \ldots$ RanF_n. Conversely, if C is a n-copula and $F_1, \ldots, F_n$ are distribution functions, then the function H defined above is a n distribution function with margins $F_1, \ldots, F_n$.

Then the quasi-inverses of $F_1, \ldots, F_n$ are $F_1^{(-1)}, \ldots, F_1^{(-n)}$ with domain $\mathbf{I}^n$, the elliptical copula determined by H is directly obtained by inverting Sklar's Theorem indicated in equation 4.1:

$$C(u_1, \ldots, u_n) = H(F_1^{(-1)}(u_1), \ldots, F_1^{(-n)}(u_n)). \tag{4.2}$$

The bivariate Gaussian copula is:

$$C(u_1, u_2) = \Phi_\rho(\Phi^{-1}(u_1), \Phi^{-1}(u_2)). \tag{4.3}$$

and the bivariate Student-t copula is:

$$C(u_1, u_2) = t_{\rho,\nu}(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2)). \tag{4.4}$$

Where ρ is the linear correlation coefficient and ν the degrees of freedom. To determine Archimedean copulas the approach is more complex. It requires the Ali-Mikhail-Haq distributions; an algrebraic method of constructing bivariate copulas among two others: inversion and geometric methods. Ali-Mikhail-Haq uses algebraic relationships between the joint distribution and the univariate margins to find copulas; this family satisfies the relationship Nelsen (2007):

$$\lambda(H(x_1, x_2)) = \lambda(F_1(x_1))\lambda(F_2(x_2)), \tag{4.5}$$

where $\lambda(t) = 1 + (1-\theta)(1-t)/t$, then on setting $\varphi(t) = -ln\lambda(t)$. H can be draft as a sum of functions of the marginals F_1 and F_2, i.e., $\varphi(H(x_1, x_2)) = \varphi(F_1(x_1)) + \varphi(F_2(x_2))$ and for copulas:

$$\varphi(C(u_1, u_2)) = \varphi(u_1) + \varphi(u_2). \tag{4.6}$$

φ is a continuous, strictly decreasing convex function from $\mathbf{I}$ to $[0, \infty]$ such that $\varphi(1) = 0, \varphi'(t) < 0$ and $\varphi''(t) > 0$ for all $0 < t < 1$. Then $\varphi^{[-1]}$ is the *pseudo-inverse* of φ defined by (4.6) with $\mathrm{Dom}\varphi^{[-1]} = [0, \infty]$ and $\mathrm{Ran}\varphi^{[-1]} = \mathbf{I}$ given by:

$$\varphi^{[-1]}(t) = \begin{cases} \varphi^{-1}(t), & 0 \leq t \leq \varphi(0), \\ 0, & \varphi(0) \leq t \leq \infty. \end{cases} \tag{4.7}$$

The conditional density of the Archimedean copula is:

$$\frac{\partial}{\partial u_2} C(u_1, u_2) = \frac{\varphi'(u_2)}{\varphi'(C(u_1, u_2))}. \tag{4.8}$$

The copula function from $\mathbf{I}^2$ to $\mathbf{I}$ is given by $C(u, v) = \varphi^{[-1]}(\varphi(u) + \varphi(v))$. This leads to the following generalization:

$$C(u_1, \ldots, u_n) = \varphi^{[-1]}(\varphi(u_1) + \cdots + \varphi(u_n)). \tag{4.9}$$

Table 4.1.: Parameters for Elliptical and some Archimedean copulas.

Name †	**Generator function**	**Parameter range**
Gaussian.		$\rho \in (-1, 1)$
Student-t.		$\rho \in (-1, 1), \nu > 2$
Clayton (1978).	$t^{-\theta} - 1$	$\theta > 0$
Gumbel (1960).	$(-ln\ t)^{\theta}$	$\theta \geq 1$
Frank (1979).	$-ln\left(\frac{e^{-\theta t} - 1}{e^{-\theta} - 1}\right)$	$\theta \in \mathbb{R} \setminus \{0\}$
Joe (1997).	$-ln[1 - (1 - t)^{\theta}]$	$\theta > 1$
Clayton-Gumbel (BB1).	$(t^{-\theta} - 1)^{\delta}$	$\theta > 0, \delta \geq 1$
Joe-Gumbel (BB6).	$(-ln[1 - (1 - t)^{\theta}])^{\delta}$	$\theta \geq 1, \delta \geq 1$
Joe-Clayton (BB7).	$(1 - (1 - t)^{\theta})^{-\delta} - 1$	$\theta \geq 1, \delta > 0$
Joe-Frank (BB8).	$-ln\left[\frac{1 - (1 - \delta t)^{\theta}}{1 - (1 - \delta)^{\theta}}\right]$	$\theta \geq 1, \delta \in (0, 1]$

† Family classes taken from Joe (1997) and Nelsen (2007). This table is not extensive refer to authors for more details.

An Archimedean copula is constructed through a generator φ.[16] Some copulas are one or two parameter(s) generator families as presented in the table 4.1.

A caveat with regard to the dimensions of Archimedean copulas should be mention: dimension 3 or higher allows only positive association, negative association works in bivariate settings. In other words, there is a practical application issue in how to identify an adequate copula. For arbitrary dimensions, the choice of an adequate copula is limited and their parametrization becomes cumbersome. This issue was noted by Aas et al. (2009). They began to use a wider class of multivariate copulas.

4.1. R-vine

A flexible graphical method proposed by various authors Joe (1996); Bedford and Cooke (2001, 2002); Kurowicka and Cooke (2006) describes multivariate copulas as a dependency model for the distribution of certain pairs of variables conditional on a specified set of variables. Using this cascade of bivariate copulas, so called *pair-copulas construction* (PCC); the recognition of the needed pairs of variables and their set of conditional variables is facilitated by an array of trees. Two classes of tree-constructions are *Canonical-vines* and *Drawable-*

[16] Details of various generators are found in Nelsen (2007).

vines or commonly known as C- and D-vine copulas.

Vines arrange the $n(n-1)/2$ pair-copulas of a n-dimensional PCC in $n-1$ linked trees. The selection of the appropriate C- and D-vine structure is important given the large number of possible choices. [17] In general, the structure captures conditional dependencies in higher trees and the order of the nodes are selected in such a way that the strongest pairwise dependencies are captured in the first tree. However, the class of C- and D-vine distributions is narrower than the class of *Real-vines* or R-vine introduced by Bedford and Cooke (2002). The latter has a enormous number of possible tree sequences to choose from. C- and D-vine are then special types of R-vine.

A D-vine is an R-vine for which the first tree has nodes with two degrees or less (path structure). A C-vine is also an R-vine which contains a node with maximal degree in each tree (star structure). Dissmann et al. (2013) suggested that it is important to work with both R-vine types as the first tree (D-vine) and the ordering of the root nodes (C-vine) determine their structure completely.

The formal definition of R-vine by Dissmann et al. (2013) specifies that $\nu = (T_1, \ldots, T_{n-1})$ is an R-vine on n elements if:

(1.) T_1 is a tree with nodes $N_1 = \{1, \ldots, n\}$ and a set of edges denoted E_1.

(2.) For $i = 2, \ldots, n-1, T_i$ is a tree with nodes $N_i = E_{i-1}$ and edge set E_i.

(3.) For $i = 2, \ldots, n-1$ and $\{a, b\} \in E_i$ with $a = \{a_1, a_2\}$ and $b = \{b_1, b_2\}$ it must hold that $\#(a \cap b = 1)$ (proximity condition), where # denotes the cardinality of the set.

The specification of the R-vine copula has the following arguments: ($\mathbf{F}$, ν, B) is an R-vine copula specification if $\mathbf{F} = (F_1, \ldots, F_n)$ is a vector of continuous invertible distribution functions, as Sklar's Theorem illustrated in equation 4.1, ν is an n-dimensional R-vine and $B = \{B_e | i = 1, \ldots, n-1; e \in E_i\}$ is a set of copula with B_e being a bivariate copula $(X_{C_{e,a}}, X_{C_{e,b}})$.
The R-vine decomposition of a multivariate density is:

$$\begin{aligned} & f(x_1, \ldots, x_n) \\ & = \prod_{k=1}^{n} f_k(x_k) \\ & \times \prod_{i=1}^{n-1} \prod_{e \in E_i} c_{C_{e,a}, C_{e,b} | D_e} \left(F_{C_{e,a}|D_e}(x_{C_{e,a}} | x_{1_{De}}, \ldots, x_{n_{De}}), F_{C_{e,b}|D_e}(x_{C_{e,b}} | x_{1_{De}}, \ldots, x_{n_{De}}) \right), \end{aligned} \tag{4.10}$$

[17] The posible choices for regular vines on n nodes is $\frac{n!}{2} \times 2^{\binom{n-2}{2}}$.

where f_k is the marginal densities $k = 1, \ldots, n$, $c_{C_{e,a},C_{e,b}|D_e}$ is the copula density of B_e for edge $e = \{a, b\}$ and $x_{i_{D,e}} \in D_e$ for $i = 1, \ldots, n$. Joe (1996) describes the strategy to obtain the conditional distributions $F_{c_{e,a}|D_e}(x_{c_{e,a}}|\cdot)$ and $F_{c_{e,b}|D_e}(x_{c_{e,b}}|\cdot)$.

This document uses the automated strategy of jointly searching for an appropriate R-vine tree structure, pair-copula families and parameter(s) values of the chosen pair-copulas as in Dissmann et al. (2013). Succinctly this is selecting which unconditional and conditional pairs of currencies to use. Subsequently finding the bivariate copula family for each pair selected using Akaike information criterion and estimating the corresponding parameter(s) in a maximum likelihood manner for each estimated copula.

The sequential method designed by the authors can be organised as follows:

(1.) Calculate the empirical Kendall's $\widehat{\tau}_{j,k}$ for all pairwise $\{j, k\}$, $1 \leq j < k \leq n$.[18]

(2.) The spanning tree that maximizes the sum of absolute empirical Kendall's taus is selected,

$$max \sum_{e=\{j,k\} \text{ in spanning tree } \widehat{\tau}_{j,k}} . \tag{4.11}$$

(3.) Subsequently, the copula family and parameter(s) are selected for each edge $\{j, k\}$ in the selected spanning tree.

(4.) Iteration is applied, based on the selected copula family and their parameter(s) in tree $i - 1$. The empirical Kendall's $\widehat{\tau}_{j,k|D}$ for all conditional variables pairs $\{j, k|D\}$ are calculated.

4.2. Empirical Copulas

Copulas' method has been applied in various empirical works. Trivedi et al. (2007); Patton (2009) provide a comprehensive survey of different copulas' applications. Chen and Poon (2007) replicated Forbes and Rigobon (2001) document using a dummied Student-t copula and two versions of time varying Student-t copula. They used world and regional risk appetite indices[19] following Wilmot et al. (2004) developed at Credit Suisse First Boston to

[18] Kendall's tau is a nonparametric measure of the degree of correlation. It measures the strength of the relationship between two ordinal level variables. Kendall's tau is used since it measures dependence independently of the assumed distribution and hence, is especially useful when combining different non-Gaussian copula families. By definition Kendall's tau is the difference between concordance and discordance probabilities of two independent random vectors. In copulas it can be: $\tau = 4 \int_0^1 \int_0^1 C(u, v) \partial C(u, v) - 1$, see Nelsen (2007) for more details.

[19] The authors illustrated that risk appetite is referred loosely to the willingness of investors to bear risk and should be distinguished from risk aversion and the riskiness of assets.

study financial crisis and contagion. For the Student-t copula the authors found a significant increase in stock market dependence in the Asian crisis and post crisis periods. Results corroborated by their risk appetite estimation.

An empirical copula approach was used by Caillault and Guegan (2005) on three Asian markets such as Thailand, Malaysia and Indonesia. These three composite indexes were expressed in Japanese currency from the period 2/Jul/1987 to 17/Dec/2002. They modelled the extreme of each markets' pair via two proposed estimators called 'naive' estimators. Then they used these estimates to determine the copula which is best adapted to the data. The authors focused on the existence of interaction between these markets rather than investigating a contagion phenomenon.

Czado et al. (2012) implemented a comprehensive solution to the selection of C-vines by identifying an appropriate structure and selecting a fitted pair-copula family. They allowed for different families and applied a C-vine structure for eight time series of US-exchange rates from different developed countries from 22/Jul/2005 until 17/Jul/2009 using an ARMA(1,1)-GARCH(1,1) model to remove time dependence. Maya et al. (2015) used a similar methodology as Czado et al. (2012) but focused on exchange rate dependence in underdeveloped countries. They applied an ARX(p)-GARCH(1,1) using data between 22/Jun/2005 and 25/Apr/2012.

4.2.1. This application

This document follows Czado et al. (2012) and Maya et al. (2015) in their application of exchange rates. The analysis is based on transformed standardized residuals to uniform margins ($u_1, u_2 \in [0, 1]$) of the filtered VARX-EGARCH model. Initially currency-pairs are constructed and their dependence observed as in figure A.10. In this matrix the half above the diagonal indicates the Kendall's tau measure of all possible pairs. With all dependences being positive. The lower half presents the level plots observed.

The sum of absolute values of this empirical Kendall's taus equation 4.11 is maximized between the Singapore dollar and every other currency in the sample. As can be calculated from the figure A.10 upper diagonal values. These pairs $e = \{j, k\}$ are presented in figure 4.1, the scatter plots are coloured as a heat-map, making it simple to analyse where the values are clustered. When points overlap the density of a particular region they become 'hot'. Additionally, the rotation of the plots is meaningful since it enables one to obtain the copula behind each dependence. Such a spin gives the survival copulas when rotation is 180 degrees. [20] 90 and 270 degrees allows for negative dependence which is not possible with the standard non-rotated versions.

[20] A survival copula and its associated copula have the same Kendall's tau.

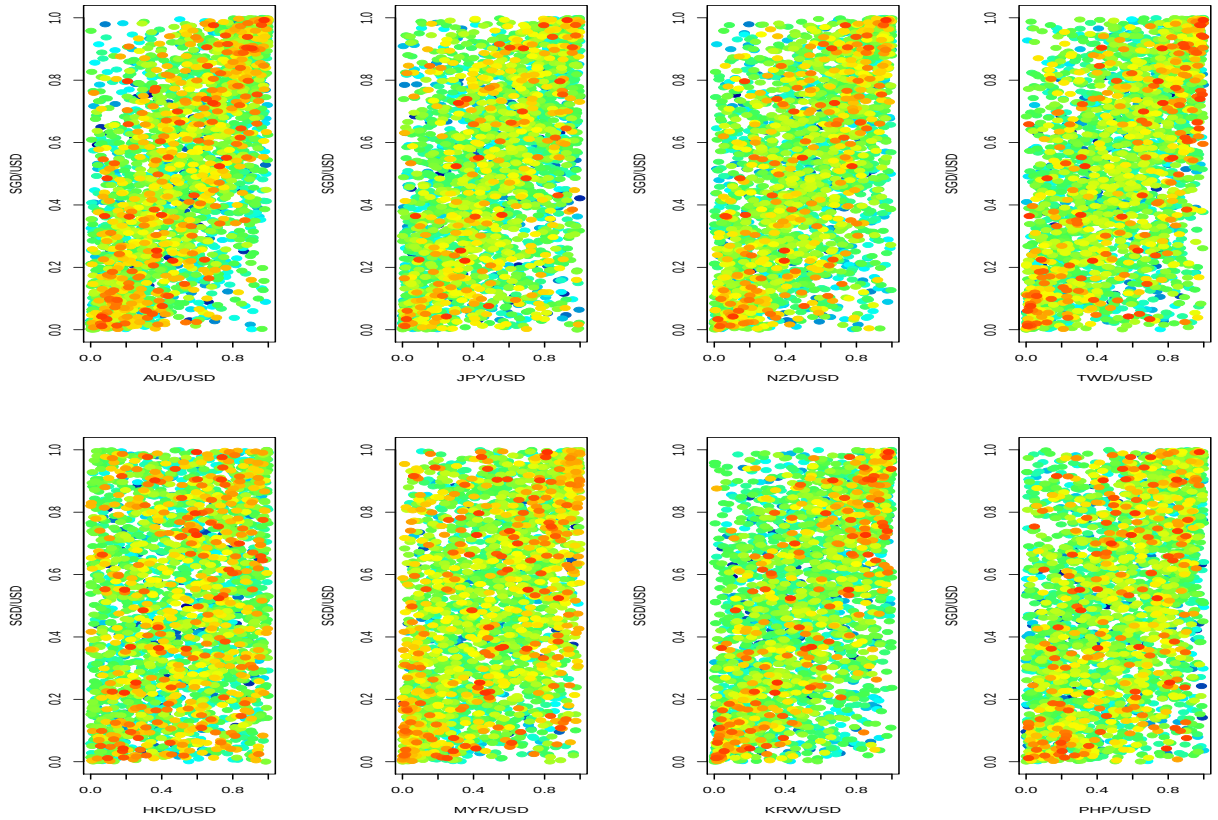

Figure 4.1.: Scatter plots for eight cases.

A maximum spanning tree (MST) algorithm of Prim was applied as Dissmann et al. (2013) prompted, in order to select the tree that maximizes the sum of absolute empirical Kendall's taus in Asian countries. The representing R-vine can be stored in an n-dimensional lower triangular matrix as Napoles (2009) proposed.

Hence for the first tree of the R-vine that often has the greatest influence on the model fit. It could be obtained from matrix M (see figure 4.2) and be graphically represented as figure 4.3. Each number corresponds to a country as established on the bottom of table 4.2. In this case the Singapore dollar is the node with the New Zealand dollar not being directly related but through the Australian dollar.

Therefore, the dependence between the Singapore dollar and the New Zealand dollar measured by the Kendall's taus is 0.06 (from table 4.2). However, if these currencies are conditioned by the Australian dollar the dependence increases to 0.10 as shown in table B.8 second tree. Although there is a higher dependence between the Australian dollar and the

New Zealand dollar (0.59) from the same table. Note that this copula selection proceeds tree by tree, since the conditional pairs in subsequent trees depend upon the specification of the previous trees through equation 4.10. These trees are shown in table B.8 for easy reading.

$$M = \begin{pmatrix} 5 & & & & & & & & \\ 8 & 1 & & & & & & & \\ 2 & 8 & 2 & & & & & & \\ 3 & 2 & 8 & 3 & & & & & \\ 4 & 3 & 7 & 8 & 4 & & & & \\ 9 & 4 & 9 & 7 & 8 & 8 & & & \\ 7 & 9 & 3 & 9 & 7 & 9 & 7 & & \\ 6 & 7 & 4 & 4 & 9 & 7 & 9 & 6 & \\ 1 & 6 & 6 & 6 & 6 & 6 & 6 & 9 & 9 \end{pmatrix}$$

Figure 4.2.: Matrix Structure.

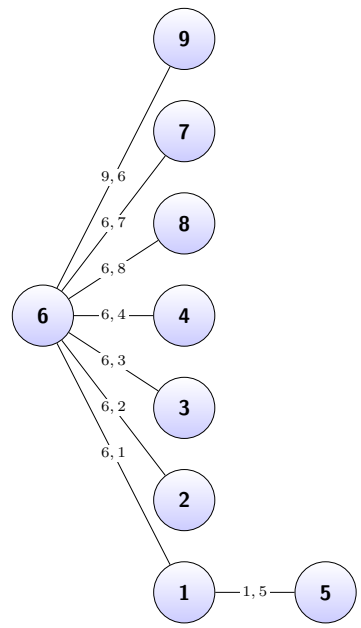

Figure 4.3.: Tree 1 from Matrix M.

Once the marginal distributions are specified, an appropriate copula is selected according to the AIC. Because copulas separate marginal distribution from dependence structures, the appropriate copula is the one which best captures dependence features between the exchange rates. The cascade of bivariate copulas (PCC), parameter(s) and Kendall's taus are estimated and disclosed in table 4.2.

Most of the estimated copulas are student-t; they have both upper and lower tail dependence of the same magnitude (due to its radial symmetry). In this case there is strong dependence in appreciations and depreciations of equal degree. The copula SSB1 or Survival Clayton-Gumbel arise in two cases (the New Zealand dollar-the Philippines peso and the Singapore dollar-the Philippines peso) with significant Kendall's taus values of 0.27 and 0.33 respectively. This copula has asymmetric tails and the dependence can be in either tail.

Other selected copulas from table 4.2 but with lower Kendall's taus values are:

(i.) A Gumbel has asymmetric tails and dependence is in the upper tail, it does not allow negative dependence. A Gumbel exhibits strong depreciation dependence and relatively weak appreciation dependence. Shocks are known to be strongly correlated

at high exchange rate values but less correlated at low exchange rate values, as in the case of Japan yen-Malaysia ringgit.

(ii.) Dependence in the tails of the Frank copula tends to be relatively weak compared to the Gaussian copula, and the strongest dependence is centered in the middle of the distribution, which suggests that the Frank copula is most appropriate for data that exhibits weak tail dependence (Malaysia ringgit-Taiwan dollar);

(iii.) A J90 or rotated Joe 90 degrees has symmetric tails but there is no tail dependence (Hong Kong dollar-Japan yen);

(iv.) A BB8-270 o Rotated Frank-Joe 270 degrees does not have tail dependence except when $\delta = 1$, then has negative dependence and concordance increases as θ or δ increases; a Tawn has asymmetric tails (Hong Kong dollar-Malaysia ringgit and Japan yen-South Korea won) and the rotated version Tawn-270 has negative dependence (Hong Kong dollar-Singapore dollar).

4.3. Tail dependence

The concept of tail dependence is used in this document as an advanced device to identify contagion among countries when extreme values occur. This measure is only copula based and can thus be used in the parametrization of copulas. Joe (1997) defines this as the amount of dependence in the upper-quadrant tail or lower-quadrant tail of a bivariate distribution.

By definition:

$$\lambda_L = \lim_{u \searrow 0} \frac{C(u,u)}{u} \tag{4.12}$$

and

$$\lambda_U = \lim_{u \nearrow 1} \frac{1 - 2u + C(u,u)}{1-u} \tag{4.13}$$

where λ_L is the lower tail and λ_U is the upper tail dependence for given bivariate copula family and parameter(s).

A copula is said to have a lower (upper) tail dependence if $\lambda_L \neq 0$ ($\lambda_U \neq 0$). The lower tail dependence measure (λ_L) is the limiting value of $\frac{C(u,u)}{u}$, which is the conditional probability $Pr[U_1 < u | U_2 < u] (= Pr[U_2 < u | U_1 < u])$ and the upper tail dependence (λ_U) is the conditional probability $Pr[U_1 > u | U_2 > u] (= Pr[U_2 > u | U_1 > u])$.

The tail dependence of a survival copula ($\bar{C}$) can denote as: $\lambda_L = \bar{\lambda_U}$ and $\lambda_U = \bar{\lambda_L}$. That is:

Table 4.2.: R-vine Estimation.

†	**Bicopula**	**Family**	**Parameter**	**Parameter2**	**Tau**
1,2	2	t	0.00198	17.78294	0.00126
1,3	2	t	0.00837	15.13470	0.00533
1,4	2	t	0.02064	15.57037	0.01314
1,5	40	BB8-270	-1.15118	-0.87202	-0.04235
1,6	2	t	-0.04162	22.87015	-0.02650
1,7	2	t	0.02060	12.48795	0.01311
1,8	2	t	0.16298	15.67622	0.10422
1,9	2	t	0.79497	7.05597	0.58503
2,3	26	J90	-1.01913	-	-0.01095
2,4	104	Tawn	1.40247	0.01575	0.01215
2,5	2	t	0.02116	12.04290	0.01347
2,6	134	Tawn-270	-1.15093	0.11914	-0.03447
2,7	2	t	-0.05020	20.20259	-0.03197
2,8	2	t	0.10769	7.88434	0.06869
2,9	2	t	0.57630	9.14128	0.39101
3,4	4	G	1.01915	-	0.01879
3,5	2	t	0.00472	13.93451	0.00300
3,6	2	t	-0.00130	18.64193	-0.00083
3,7	104	Tawn	1.13522	0.15702	0.03831
3,8	2	t	0.03586	11.32560	0.02283
3,9	2	t	0.20187	9.79871	0.12941
4,5	2	t	0.08787	13.79264	0.05601
4,6	2	t	-0.03069	8.38134	-0.01954
4,7	2	t	0.01611	16.00276	0.01025
4,8	5	F	-0.56044	-	0.06207
4,9	2	t	0.46698	6.83189	0.30932
5,6	2	t	0.10449	12.70375	0.06664
5,7	2	t	0.14686	11.43115	0.09383
5,8	2	t	0.21649	12.99042	0.13892
5,9	17	SBB1	0.20375	1.25177	0.27499
6,7	2	t	0.07779	12.49939	0.04957
6,8	2	t	0.30560	8.40753	0.19772
6,9	17	SBB1	0.28064	1.30983	0.33049
7,8	2	t	0.19643	14.49923	0.12586
7,9	2	t	0.51890	6.05542	0.34732
8,9	2	t	0.37659	11.87665	0.24580

† 1: Australia, 2: Hong Kong, 3: Japan, 4: Malaysia, 5: New Zealand, 6: Singapore, 7: South Korea, 8: Taiwan, 9: The Philippines.

Table 4.3.: Tail Dependence.

Currency	AUD/USD.	HKD/USD.	JPY/USD.	MYR/USD.	NZD/USD.	SGD/USD.	KRW/USD.	TWD/USD.	PHP/USD.
AUD/USD.		0.0003733	0.0010532	0.0009961	0.00	0.0000333	0.0030743	0.0030348	0.3653352*
HKD/USD.	0.0003733		0.00	0.0136382***	0.0036371	0.00	0.0000850	0.0256844***	0.1293196*
JPY/USD.	0.0010532	0.00		0.0258808***	0.0015974	0.0002629	0.0500887**	0.0052101	0.0218011***
MYR/USD.	0.0009961	0.00	0.00		0.0031408	0.0110040***	0.0008183	0.00	0.1309164*
NZD/USD.	0.00	0.0036371	0.0015974	0.0031408		0.0050539	0.0098951	0.0095238	0.0660321**
SGD/USD.	0.0000333	0.00	0.0002629	0.0110040***	0.0050539		0.0045294	0.0508772**	0.1517370*
KRW/USD.	0.0030743	0.0000850	0.00	0.0008183	0.0098951	0.0045294		0.0054555	0.1782619*
TWD/USD.	0.0030348	0.0256844***	0.0052101	0.00	0.0095238	0.0508772**	0.0054555		0.0313684***
PHP/USD.	0.3653352*	0.1293196*	0.0218011***	0.1309164*	0.2602656*	0.3024505*	0.1782619*	0.0313684***	

*** If λ_L or $\lambda_U \geq Pr[1\%]$.
** If λ_L or $\lambda_U \geq Pr[5\%]$.
* If λ_L or $\lambda_U \geq Pr[10\%]$.

$$\lambda_L = \lim_{u \searrow 0} \frac{C(u,u)}{u} = \lim_{v \nearrow 1} \frac{C(1-v,1-v)}{1-v} = \lim_{v \nearrow 1} \frac{1-2v+\bar{C}(v,v)}{1-v} = \bar{\lambda_U} \tag{4.14}$$

$$\lambda_U = \lim_{u \nearrow 1} \frac{1-2u+C(u,u)}{1-u} = \lim_{u \searrow 0} \frac{2v-1+C(1-v,1-v)}{v} = \lim_{u \searrow 0} \frac{\bar{C}(v,v)}{v} = \bar{\lambda_L} \tag{4.15}$$

The interpretation of the coefficients of tail dependency is that it measures the probability of two random variables both taking extreme values. The upper tail dependence of the nine Asian exchange rates are displayed in the top right panel of table 4.3. Upper tail dependence is associated with currencies co-movement for large depreciations. On the other hand, lower tail dependence indicates large appreciations as shown on the bottom panel in the same table.

From table 4.3 some important observations can be established. Tails values registered in the table are mainly symmetric. The pair countries with both tails equal to zero ($\lambda_L = 0$ and $\lambda_U = 0$) as in Gaussian copulas are: Australian dollar-New Zealand dollar, Hong Kong dollar-(Japan yen, Singapore dollar) and Malaysia ringgit-Taiwan dollar. In other words for these four cases there is not contagion from large appreciations or depreciations. This finding then encourages the same results as Forbes and Rigobon (2001); Basu (2002); Bordo and Murshid (2000).

Some pairs show only upper tail ($\lambda_L = 0$): Hong Kong dollar-Malaysia ringgit, Japan yen-(Malaysia ringgit and South Korea won). These exchange rates exhibits asymmetric behaviour just in devaluation episodes as there are not cases of exchange rate with only lower tail ($\lambda_U = 0$).

Furthermore, the highest six tail values ($\lambda_L \neq 0$ or $\lambda_U \neq 0$) in descending order are between The Philippines peso- and the following: Australian dollar, Singapore dollar, New Zealand dollar, South Korea won, Malaysia ringgit and Hong Kong dollar. These values are registered in the bottom row or last column from table 4.3. Thus, The Philippines peso highly

co-moves to appreciations and depreciations with other six currencies in the region.

From this group, the asymmetric tails are The Philippines peso-(Singapore dollar and New Zealand dollar) with $\lambda_L = (0.30 \text{ and } 0.26)$; and depreciation probability of $\lambda_U = (0.15 \text{ and } 0.06)$ respectively. This outcome has relevance as The Philippines peso showed to have the heaviest tails in the sample as described in the analysis of normality in the data (see table B.6).

Australian dollar, Japan yen and New Zealand dollar have only one significant case in upper and lower tail dependence. These currencies are moderately independent from movements in other currencies as their conditional probability is lower than one percent. These currencies are also among the pairs with no-tails (upper and lower) described above. In addition Australian dollar and New Zealand dollar were referenced earlier for their platykurtic distribution where appreciations or devaluations in extreme episodes are absent. In consequence it appears to be a block of currencies with dependence lower than 1% and other block of currencies with significant dependence ($> 1\%$).

In table 4.3 the top right panel probabilities are higher than 1% for 38.88 percent of the cases and 30.55 percent for lower tail values on the bottom half of the diagonal. Therefore, Asian exchange rates presented contagion in periods of large depreciation as well as evidence of contagion during periods of large currency appreciations. As the level of exchange rate market contagion gives information about how possible it is that currency crises spill over from one country to another. It is not clear for Asian currencies to be more sensible to appreciations or depreciations. Moreover, this highlights the 'fear of floating' argument as exchange rates could be managed or pegged in order to avoid contagion.

This results could exhibit the dynamics of different regions with diverse economic structures and policies. For instance, Maya et al. (2015) conducted a regular vine copula approach for six Latin American exchanges rates. These authors use a tail dependence coefficient base on Caillault and Guegan (2005). They find that these currencies were correlated in large appreciations characterised by significant lower tail dependence. Thus, Latin American exchange rates presented contagion in periods of large appreciation and no evidence of contagion during periods of currency deprecations.

In this document most tail dependence are symmetric in contrast to the findings of Maya et al. (2015). Moreover, extreme returns are not as atypical as expected by contagion defined in this document. The sample data can be reduced to account for a different exchange regimen set up. An additional exercise can be performed from 26/Jul/2005 to 15/Mar/2017, as Malaysia changed the arrangement to a managed float in 2005 (see table 4.4) to verify the robustness on the results.

Table 4.4.: Tail Dependence (2005-2017).

Currency	AUD/USD.	HKD/USD.	JPY/USD.	MYR/USD.	NZD/USD.	SGD/USD.	KRW/USD.	TWD/USD.	PHP/USD.
AUD/USD.		0.0029639	0.0010631	0.00	0.0005575	0.0004846	0.0003091	0.0035372	0.2469150*
HKD/USD.	0.0029639		0.0363367 ***	0.0370894***	0.0064438	0.0030311	0.00	0.00	0.0404907***
JPY/USD.	0.0010631	0.00		0.00	0.00	0.00	0.0531817**	0.0051655	0.0216218***
MYR/USD.	0.0354553***	0.00	0.00		0.00	0.0005604	0.0095641	0.00	0.1552480*
NZD/USD.	0.0005575	0.0064438	0.00	0.0172193 ***		0.0000336	0.0027471	0.00	0.0441363***
SGD/USD.	0.0004846	0.0030311	0.00	0.0005604	0.0000336		0.0000545	0.0079833	0.048249***
KRW/USD.	0.0003091	0.00	0.00	0.0095641	0.0027471	0.00		0.0773933**	0.1389989*
TWD/USD.	0.0035737	0.0364114***	0.0051655	0.00	0.00	0.0079833	0.0773933 **		0.1259573*
PHP/USD.	0.2469150*	0.0404907***	0.0216218 ***	0.1552480*	0.0441363***	0.0482490***	0.1389989*	0.1259573*	

*** If λ_L or $\lambda_U \geq Pr[1\%]$.
** If λ_L or $\lambda_U \geq Pr[5\%]$.
* If λ_L or $\lambda_U \geq Pr[10\%]$.

4.3.1. Robust analysis

From table 4.4 pair countries with both tails equal to zero increases to six cases: Hong Kong dollar-South Korea won, Japan yen-(Malaysia ringgit, New Zealand dollar and Singapore dollar) and Taiwan dollar-(Malaysia ringgit and New Zealand dollar). As oppose to table 4.3 there are cases of only lower tail: Hong Kong dollar-Taiwan dollar and Malaysia ringgit-(Australia dollar and New Zealand dollar).

Pairs with only upper tail are: Hong Kong dollar-(Japan yen and Malaysia ringgit) and South Korea won-(Japan yen and Singapore dollar). The relation Hong Kong dollar-Japan yen becomes assymetric with probability of 0.03 in the upper tail. Ito (2017) describes that the diversity in monetary and exchange rate regimes may produce large changes and differing movements in intra-regional cross rates; as in the case of Japanese yen/Korean won rate. For example, the collapse of Lehman Brothers in September 2008 caused an appreciation of the Japanese yen (safe haven currency) and a depreciation of the Korean won. This means that depreciation can be found among these currencies. [21]

In table 4.4 probabilities higher than 1% for upper and lower tails are equal at 33.33 percent. This result is robust compared to 38.88 and 30.55 percent for upper and lower tails respectively as in table 4.3. The Philippines peso continues to have the highest coefficients. Moreover, tails in tables 4.3 and 4.4 maintained symmetry for most cases. An interpretation of this phenomenon could be that interventions from Central Banks are necessary to avoid sudden swings in the exchange rates.

As Levy-Yeyati (2007) explained, such interventions can be limited contrary to the believe

[21] Competitive devaluation is referred by Claessens et al. (2001) as the cases of Taiwan and Singapore when their exchange rate depreciated dramatically during the Asian crisis. Despite them having safe and sound fundamentals. It is possible that competitive devaluation could certainly have deepened the crisis and frightened foreign investors.

that many pegs generally exhibit heavier intervention than 'typical' free floating arrangements like Australia dollar or Japan yen. This might reflect the success of pegs in taking off market pressure when it will not be subject to considerable shocks.

However, there are different incentives and implications to interventions; in the case of appreciations (λ_L) there is a long-term economic growth rationale; whereas in depreciation episodes (λ_U) the focus is on short-run financial crises. From the results it appears that Asian currencies manage both cases. Therefore monetary authorities are containing contagion and reducing systematic risk. As investors benefit greatly in their portfolio allocation as risk of contagion is dwindle.

Furthermore, following the Asian crisis of 1997-1998 and the dissatisfaction with the way the IMF handled the crisis, particularly in Thailand and Indonesia (it has been claimed that several IMF misjudgements actually exacerbated the crises in the countries where they intervened), central banks and governments in East Asia agreed to create a regional self-help mechanism for effective prevention and management of financial crises which included regional economic surveillance led by the Economic Review and Policy Dialogue (ERPD), a regional liquidity support for economies facing short term needs for foreign exchange reserves, called the Chiang Mai Initiative (CMI), and the Asian Bond Market Initiative (ABMI) to promote development of domestic capital markets. This reality could also explain the symmetries found in this document.

In particular the CMI intended to reduce the risk of currency crises and manage such crises or crisis contagion. The CMI is comprised of two elements: (a.) The expansion of the ASEAN Swap Arrangment (ASA) and (b.) The creation of a new network of bilateral swap arrangments (BSAs) among ASEAN plus three members. Kawai (2010) considers that the total amount of bilateral currency swaps by April 2009 was $90 billion and the total ASA stood at $2 billion. Neither not negligible amounts when considering the analysis carried out in this document and the results obtained in the tail dependences.

5. Conclusions

In order to test for contagion between nine Asian nominal exchange rates with different arrangements a synchronized period from 10/Dec/1996 to 15/Mar/2017 for daily closing values was taken; a linear and no-linear approach were used. A VARX-EGARCH was used in order to model each currency's volatility and the feedbacks to news and innovations, the appropriateness of this model was justified compare to different econometric techniques and the adequate economic theory. In the Copula segment the theorem of Sklar (1959), the automated strategy of Dissmann et al. (2013) and the tail dependence criterion proposed by Cherubini et al. (2004) were used. Some interesting findings can be highlighted from this comprehensive study. Succinctly:

(i.) The majority of tails are symmetric as in tables 4.3 and 4.4; this validates the numerous elliptical student-t copulas in table 4.2. Due to this symmetric feature probabilities in appreciation and depreciation higher than one percent for the nine currencies are at 30.5 and 38.8 percent respectively. This highlights the 'fear of floating' argument as exchange rates could be handled in order to avoid episodes of contagion. Furthermore, The Philippines peso highly co-moves to appreciations and depreciations with other six currencies in the region. It has the heaviest tails in the sample.

(ii.) Australian dollar, Japan yen and New Zealand dollar assemble a block of currencies with probability lower than one percent and moderate dependence from other currencies. Moreover, no contagion is found among Australian dollar-New Zealand dollar, Hong Kong dollar-(Japan yen, Singapore dollar) and Malaysia ringgit-Taiwan dollar. Both tails are equal to zero for these pairs. This outcome pitches that diverse exchange rate arrangements as used in this document have no influence in the analysis.

(iii.) Symmetric tails as in student-t copulas could reveal Central Bank's intervention by avoiding sudden swings in the exchange rates. In interventions for appreciations (λ_L) there is a long-term economic growth purpose; in depreciations (λ_U) the focus is on short-run financial crises. Therefore, exchange rate steadiness is a public good for regional growth and economic stability. Moreover, intra-regional exchange rate stability is extremely important given numerous trade, investment, financial linkages and the fact that crisis contagion tends to be concentrated, and economic spill-overs are significant; this requires closer policy coordination among the financial and monetary authorities.

(iv.) The information criteria can determine if contagion identification in tail dependence or first moment modelling is more appropriate. For the model VARX(p,s), AIC is -99.23 as in table 3.3 and the R-vine has AIC equal to -8310.48 as in table B.8. This document included both methods.

(v.) This document went beyond the vanilla GARCH modelling by using an EGARCH for volatility dependence. An interesting finding is that the GARCH term is significant for all countries at 1% as in table B.7. The ARCH terms are not significant for every country aside Japan at 5% and Hong Kong at 10% confidences. The asymmetry term is exclusively not significant for Taiwan. South Korea recorded significance at 5%; the remaining detailed at 1%.

(vi.) Several directions for future research can be suggested to this work. The most important is to implement a dynamic conditional correlations (DCC), this can correct for constant correlation over time. This model is appropriate for measuring time-varying conditional correlations and the responses to news and innovations. In addition to that, several multivariate copulas have been developed that incorporate time-varying that can improve the model fit; such copulas are called cDCC.

A. Appendix: Graphics

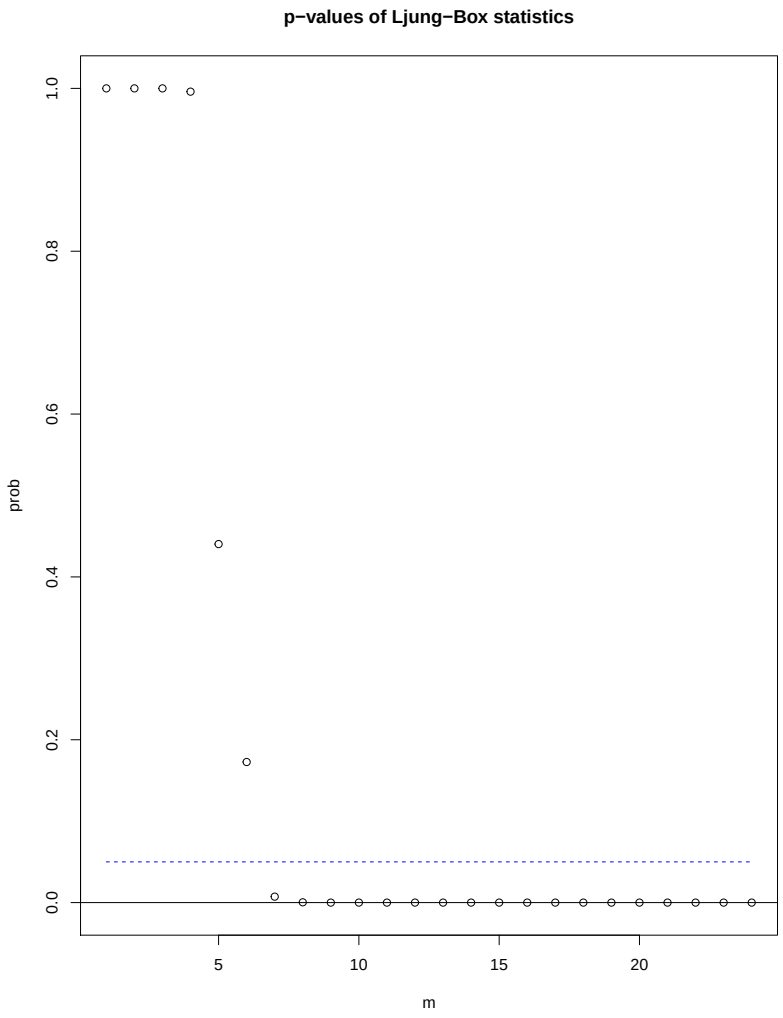

Figure A.1.: *p-values* of Multivariate Ljung-Box of Residuals.

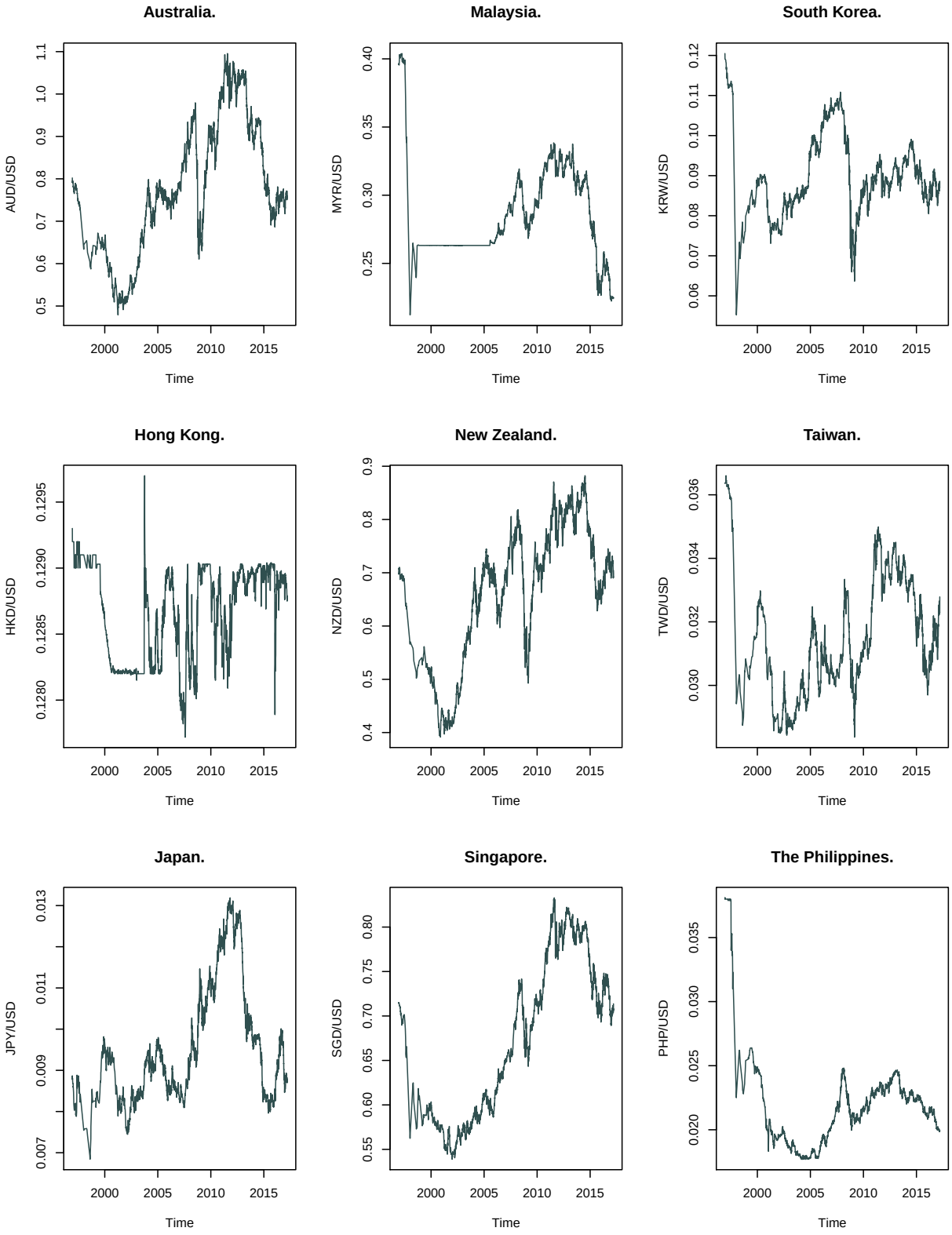

Figure A.2.: Nominal Exchange Rates 1996-2017.

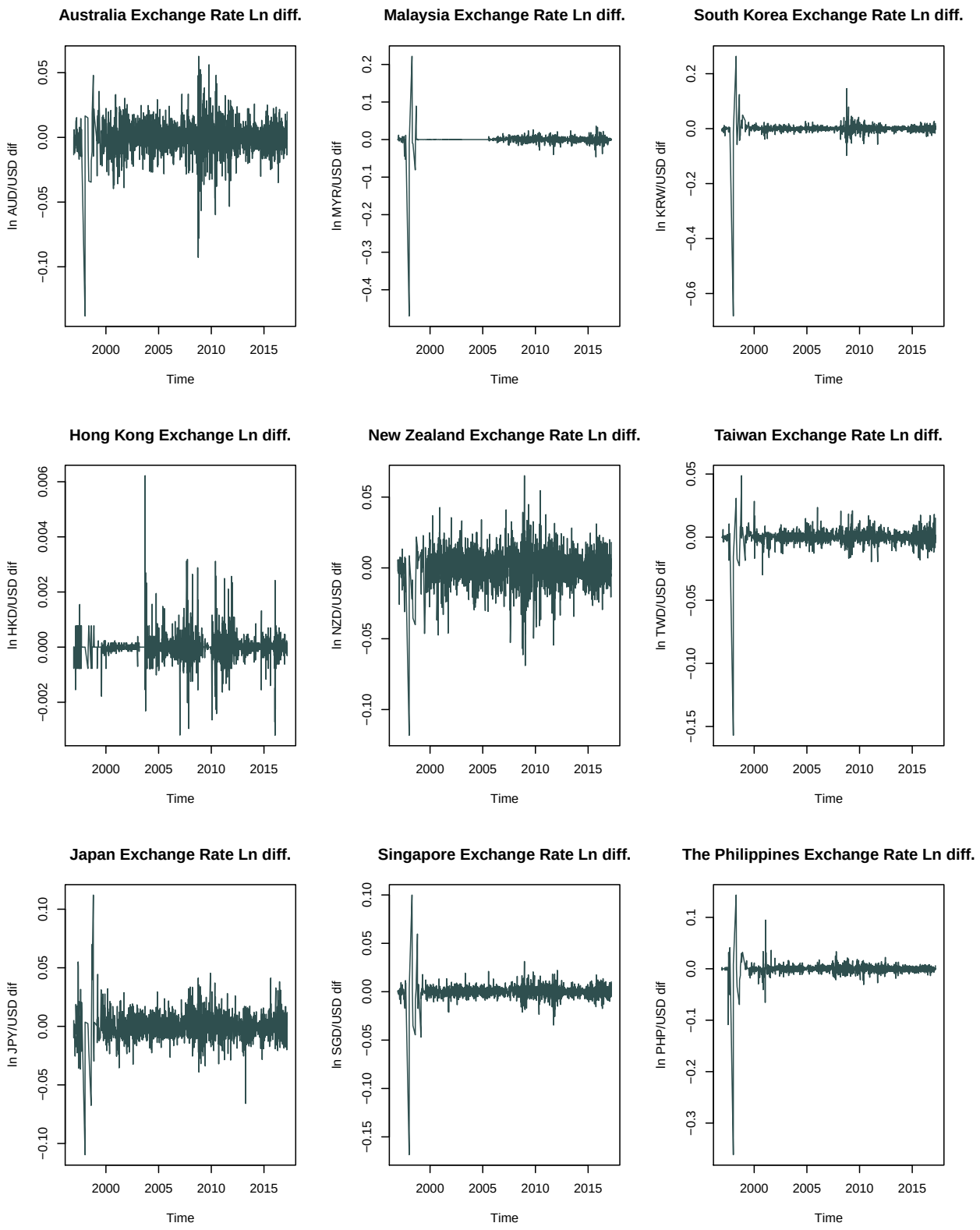

Figure A.3.: Ln Diff. Nominal Exchange Rates 1996-2017.

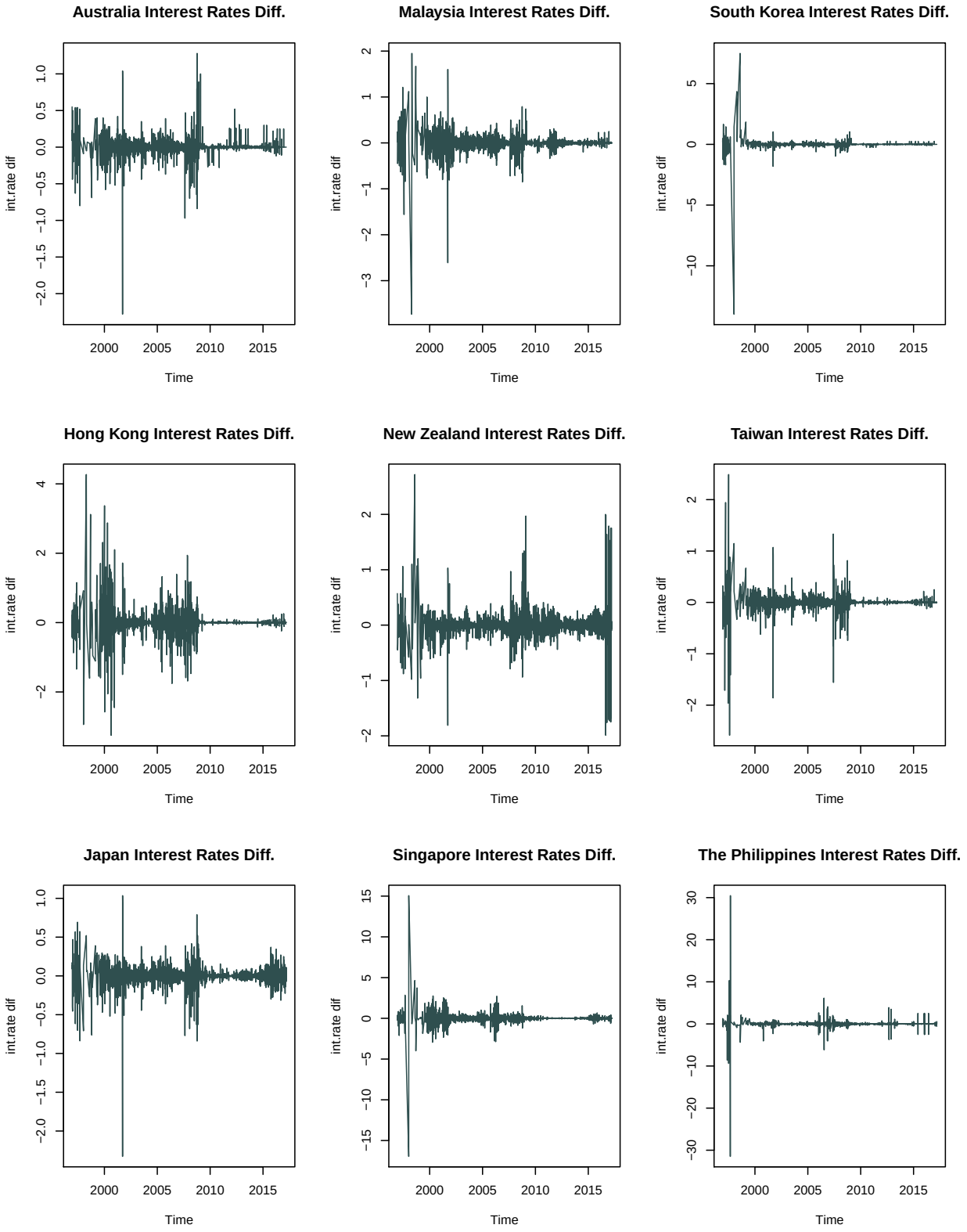

Figure A.4.: Diff. Spread Interest Rates 1996-2017.

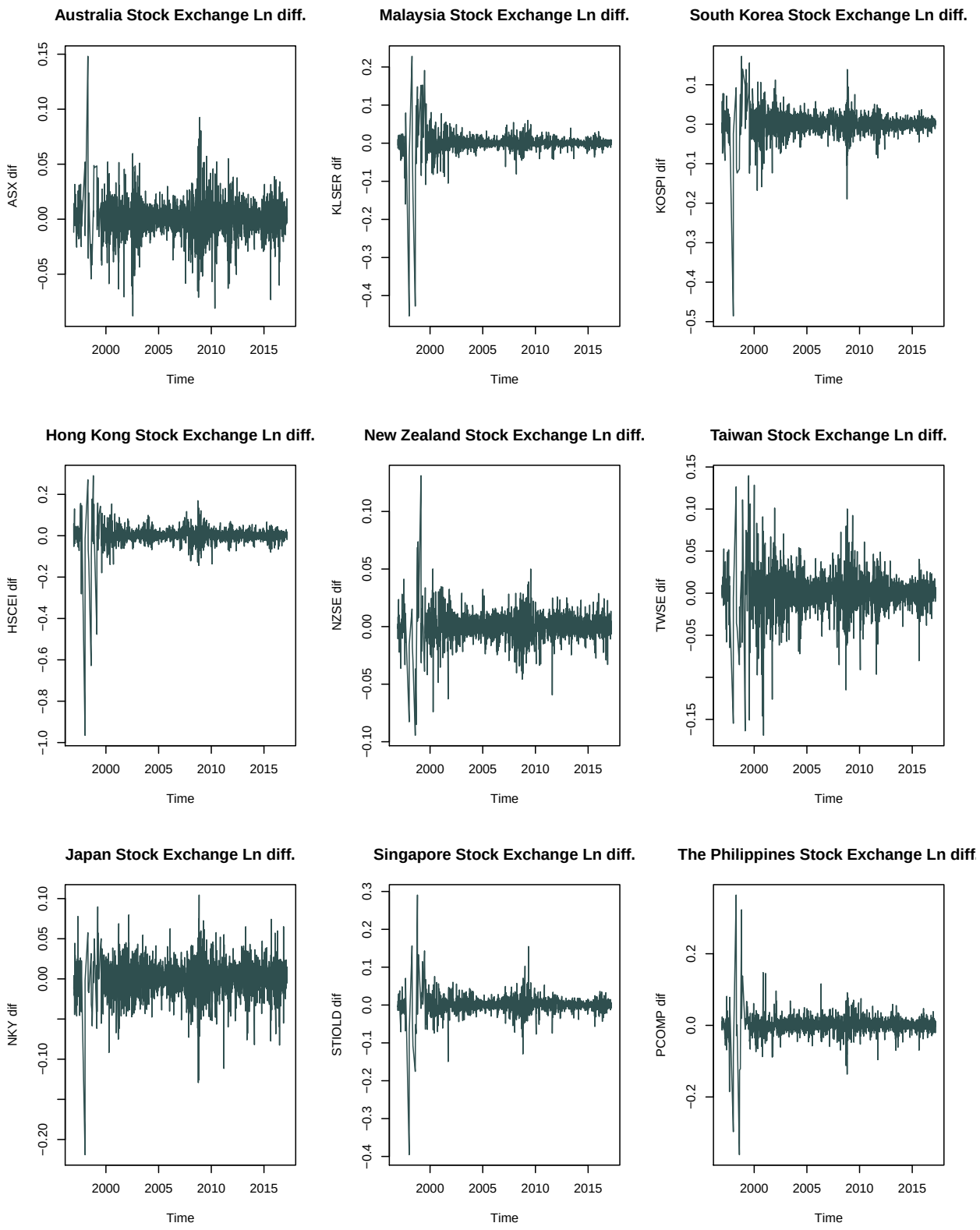

Figure A.5.: Ln Diff. Stock Market Indexes 1996-2017.

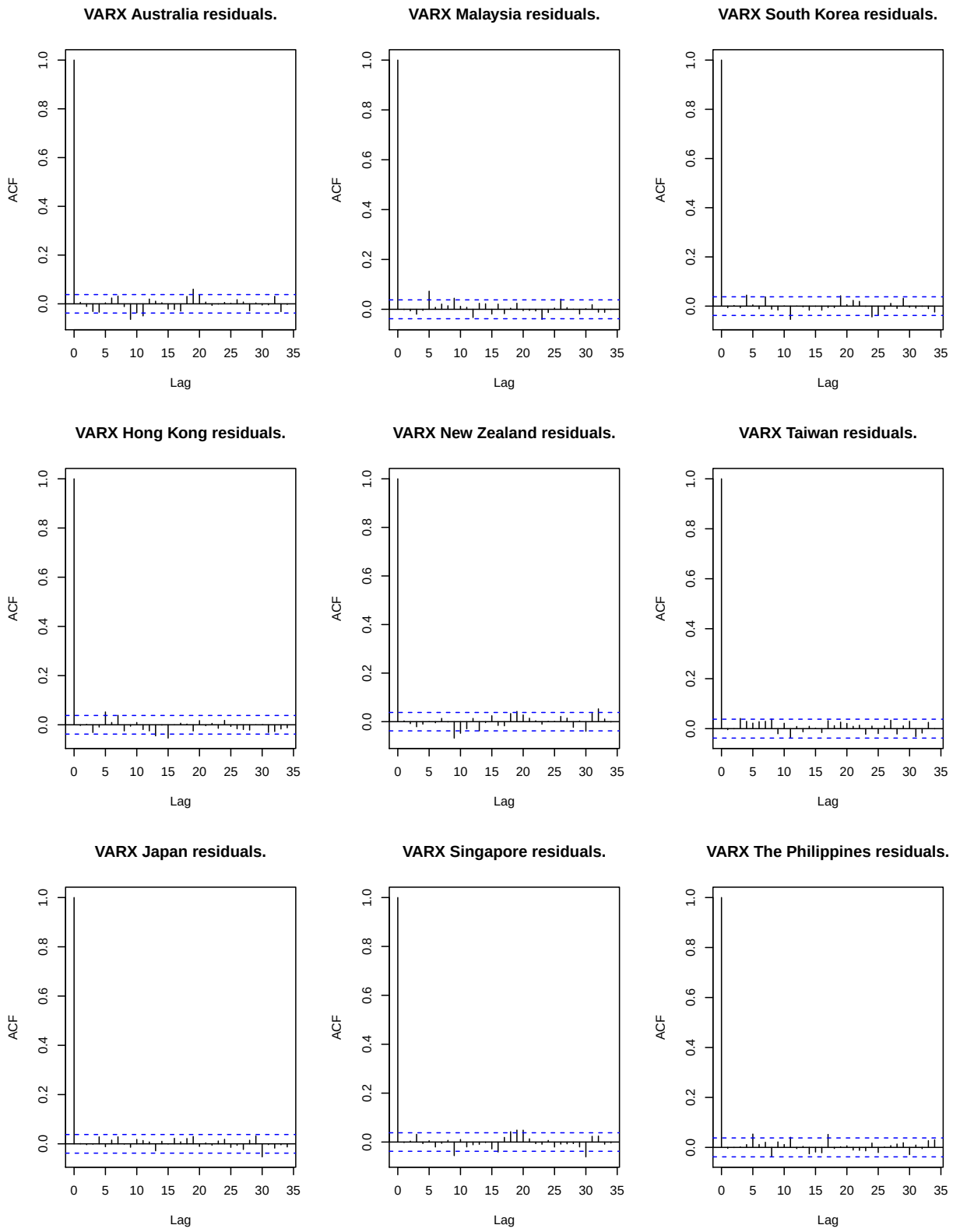

Figure A.6.: ACF VARX(p,s) Residuals.

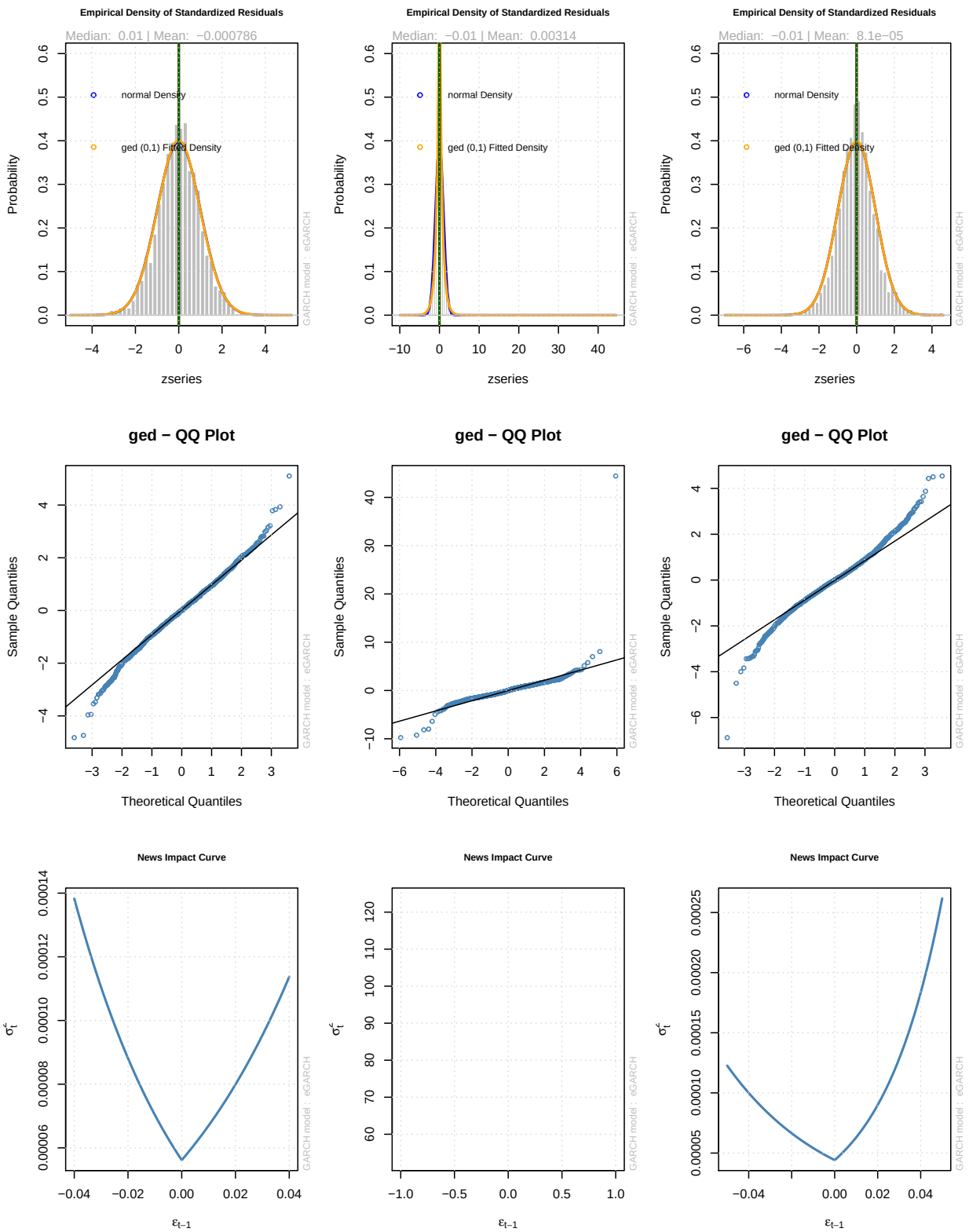

Figure A.7.: Australia (left), Hong Kong (center) and Japan (right).

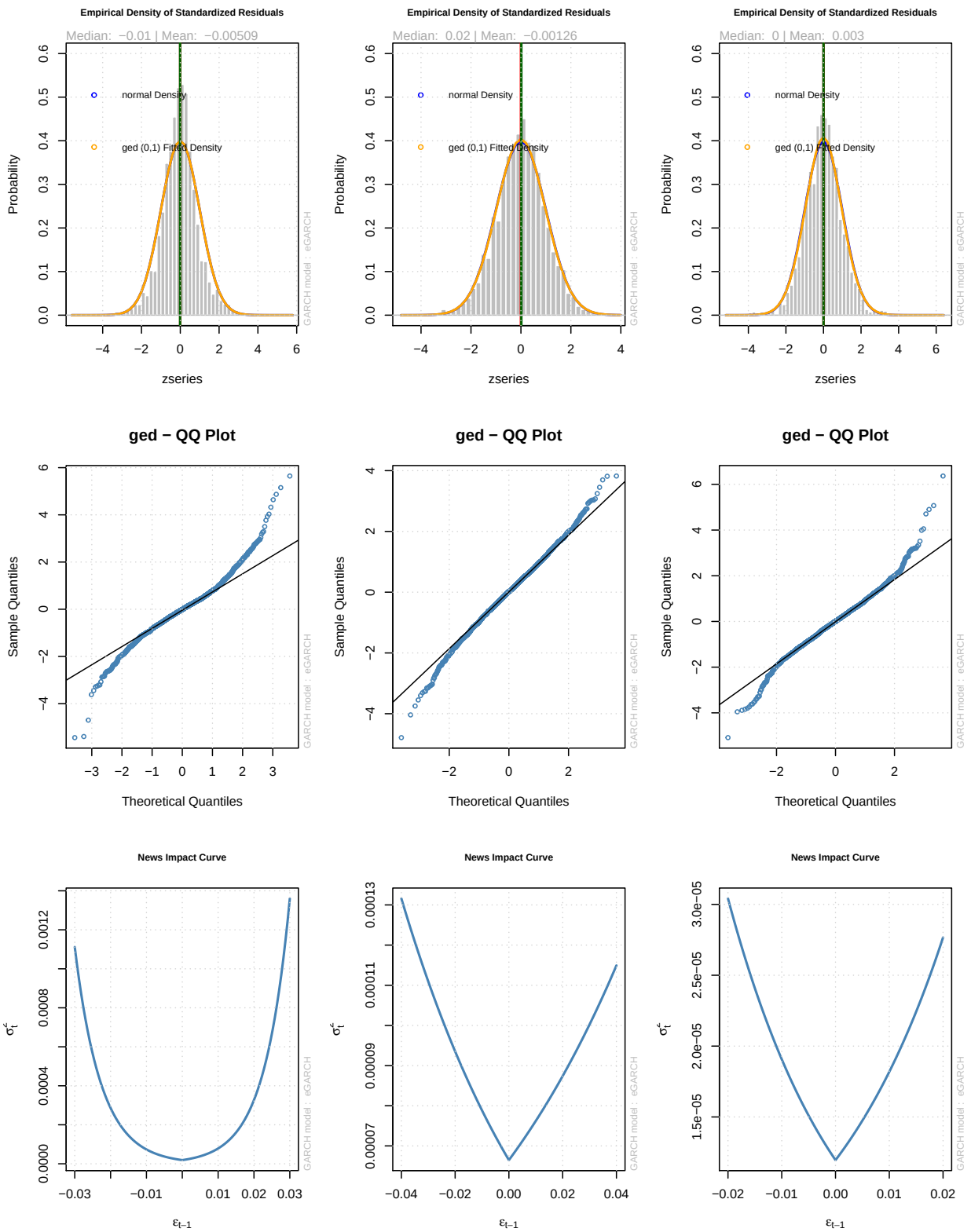

Figure A.8.: Malaysia (left), New Zealand (center) and Singapore (right).

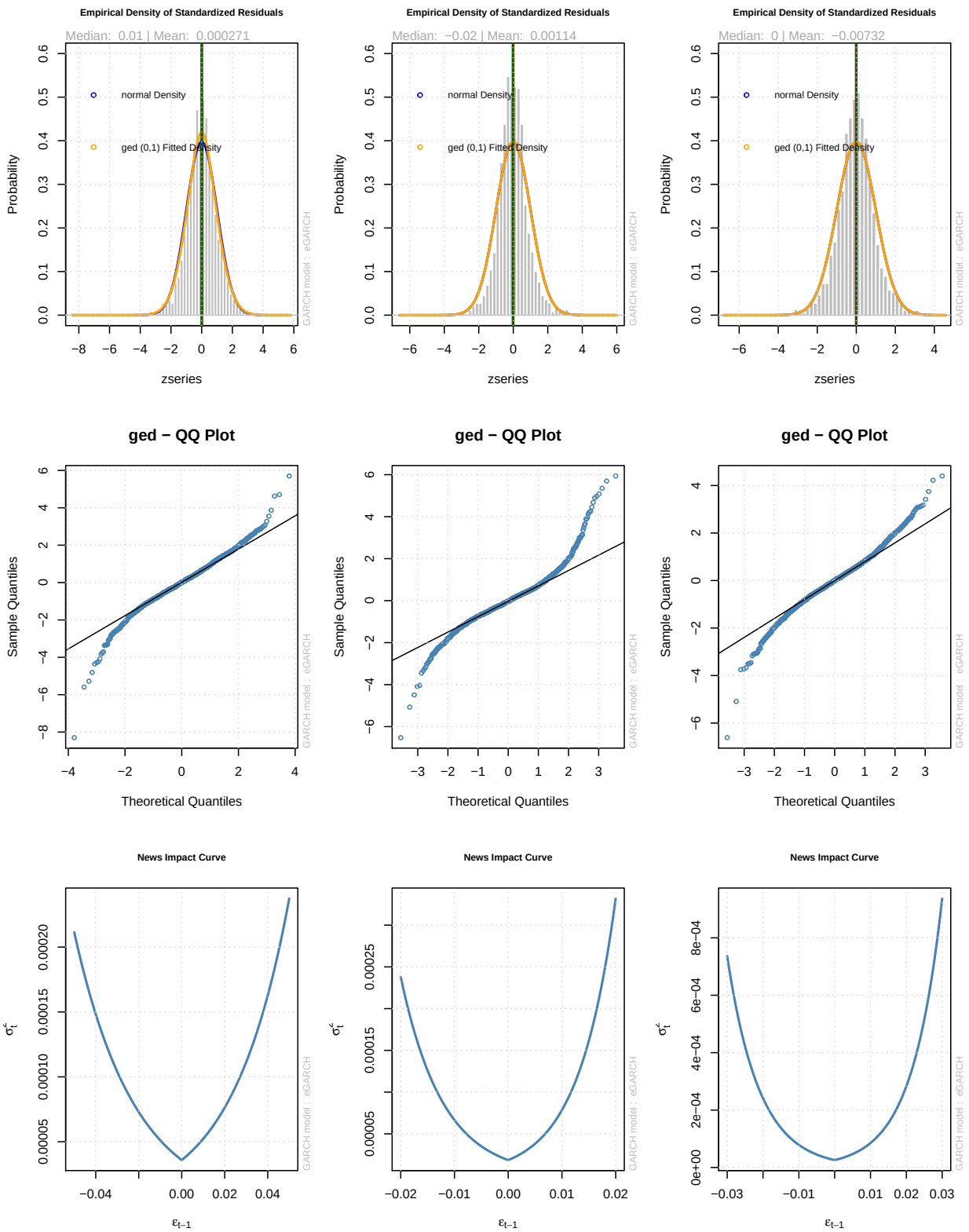

Figure A.9.: South Korea (left), Taiwan (center) and The Philippines (right).

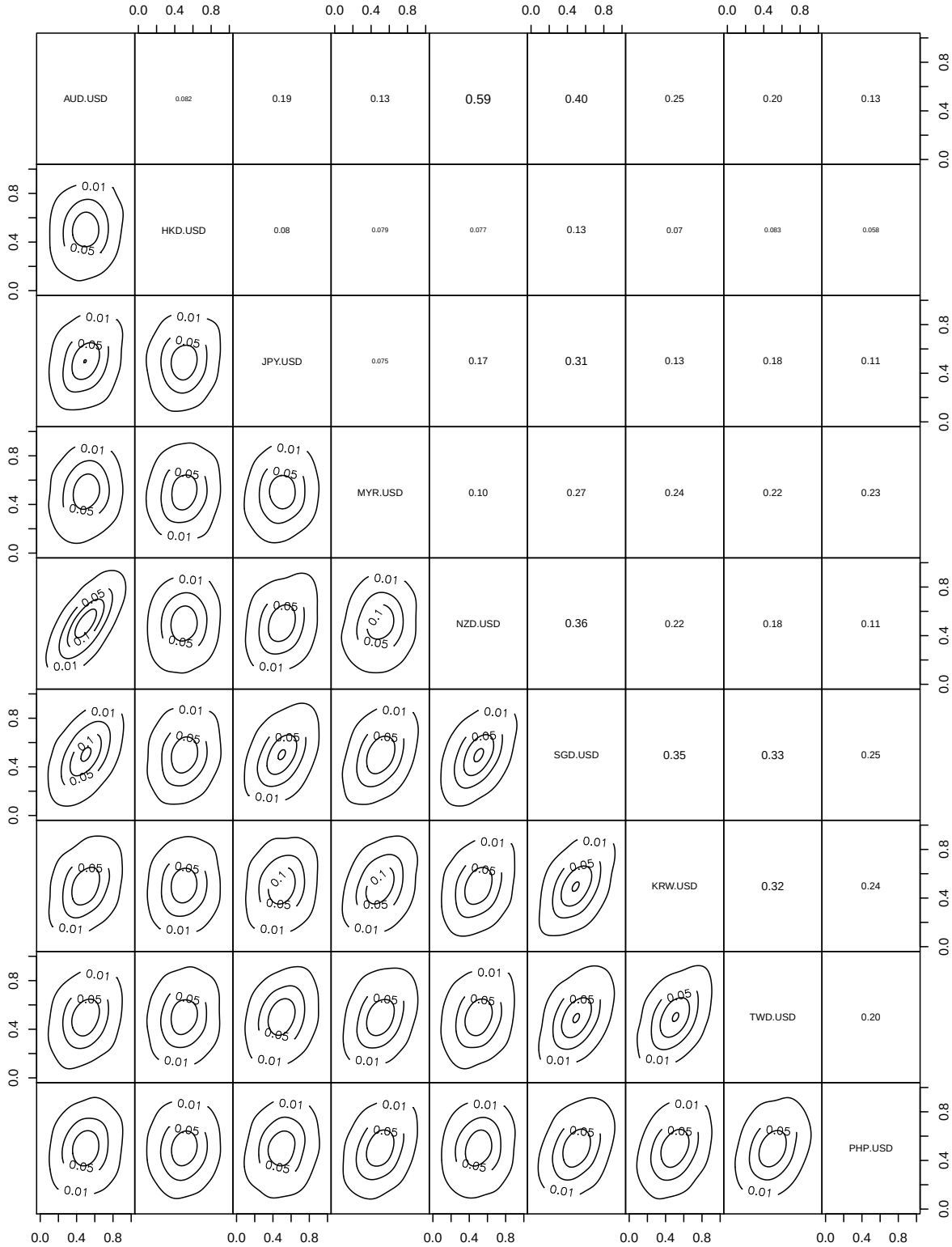

Figure A.10.: Kendall's tau and contours.

B. Appendix: Tables

Table B.1.: Ln Diff. Exchange rate tests.

Test types / **Country**	**Ljung-Box** χ^2	**Augmented Dickey-Fuller**	**KPSS**
Australia.	62.333	-10.294	0.12458
Hong Kong.	50.488	-12.459	0.050129
Japan.	68.774	-11.662	0.094698
Malaysia.	376.47	-11.142	0.18228
New Zealand.	49.147	-10.571	0.11363
Singapore.	231.52	-10.497	0.27273
South Korea.	288.03	-11.878	0.083531
Taiwan.	114.26	-10.745	0.19525
The Philippines.	215.13	-11.513	0.55369

Table B.2.: Diff. Spread Interest rate tests.

Test types / **Country**	**Ljung-Box** χ^2	**Augmented Dickey-Fuller**	**KPSS**
Australia.	194.08	-10.204	0.28492
Hong Kong.	284.46	-14.942	0.0064867
Japan.	249.22	-9.9242	0.23594
Malaysia.	496.63	-9.2219	0.15818
New Zealand.	495.32	-12.957	0.11193
Singapore.	677.75	-17.221	0.011694
South Korea.	348.81	-15.164	0.06246
Taiwan.	400.7	-11.993	0.07075
The Philippines.	771.61	-12.065	0.0051147

Table B.3.: Ln Diff. Stock Market Index tests.

Country \ Test types	**Ljung-Box** χ^2	**Augmented Dickey-Fuller**	**KPSS**
Australia.	50.22	-11.312	0.046582
Hong Kong.	237.28	-12.178	0.066525
Japan.	50.761	-10.936	0.27911
Malaysia.	308.88	-12.488	0.11606
New Zealand.	51.564	-12.299	0.13101
Singapore.	145.13	-12.481	0.031733
South Korea.	93.248	-13.845	0.023727
Taiwan.	40.714	-11.187	0.044294
The Philippines.	97.096	-13.184	0.30229
S&P500.	78.294	-10.149	0.078255
VIX.	88.194	-12.965	0.017425

Table B.4.: Granger Causality test (opposite causality).

Country \ Granger test	**Diff. Spread Interest rate**		**Ln Diff. Stock Market Index**	
	F.Statistic	p-value	F.Statistic	p-value
Australia.	3.46582	3.e-08***	3.64599	6.e-09***
Hong Kong.	1.09780	0.3369	1.68752	0.0196**
Japan.	2.38019	0.0002***	6.00376	2.e-18***
Malaysia.	25.9250	4.e-103***	36.7108	2.e-145***
New Zealand.	2.91472	3.e-06***	2.35023	0.0002***
Singapore.	4.65345	6.e-13***	9.24540	2.e-32***
South Korea.	8.49581	4.e-29***	9.07322	1.e-31***
Taiwan.	3.77479	2.e-09***	5.83964	8.e-18***
The Philippines.	10.7300	8.e-39***	15.6735	3.e-60***

*** Null hypothesis rejected at 1%.

** Null hypothesis rejected at 5%.

Note: This table shows opposite causality of table 3.1

Table B.5.: Multivariate Ljung-Box Tests for Residuals.

m	**Q(m)**	**df**	**p-value**
1	2.97	81	1.00
2	11.19	162	1.00
3	113.63	243	1.00
4	260.53	324	1.00
5	408.62	405	0.44
6	515.33	486	0.17
7	652.54	567	0.01
8	776.71	648	0.00
9	901.58	729	0.00
10	987.52	810	0.00
11	1102.40	891	0.00
12	1190.90	972	0.00
13	1291.51	1053	0.00
14	1371.46	1134	0.00
15	1484.14	1215	0.00
16	1581.73	1296	0.00
17	1679.85	1377	0.00
18	1762.85	1458	0.00
19	1852.67	1539	0.00
20	1944.38	1620	0.00
21	2042.55	1701	0.00
22	2125.45	1782	0.00
23	2218.53	1863	0.00
24	2291.10	1944	0.00

Table B.6.: Nominal Exchange Rates. Descriptive Statistics

	AUD/USD	**HKD/USD**	**JPY/USD**	**MYR/USD**	**NZD/USD**	**SGD/USD**	**KRW/USD**	**TWD/USD**	**PHP/USD**
Mean.	0.786975	0.128649	0.009510	0.283333	0.677752	0.678822	0.090357	0.031462	0.021449
Median.	0.764900	0.128770	0.009182	0.271076	0.695000	0.691300	0.088795	0.031242	0.021373
Maximum.	1.095600	0.129700	0.013188	0.403926	0.882300	0.832900	0.120480	0.036603	0.038100
Minimum.	0.479000	0.127720	0.006842	0.212202	0.391500	0.538900	0.055240	0.028373	0.017700
Std.Dev.	0.148636	0.000341	0.001352	0.031989	0.119821	0.087803	0.009160	0.001770	0.003200
Skewness.	0.080284	-0.356226	1.138913	0.944481	-0.595778	0.073420	0.403274	0.367695	2.570553
Kurtosis.	2.275234	1.711320	3.451731	4.505236	2.579427	1.544966	3.318169	2.475451	14.22112
Jarque-Bera.	62.08701	244.2935	607.5612	658.87	179.8933	240.9587	84.69722	91.93031	17164.14
Probability.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kolmogorov-Smirnov.	0.68734	0.55081	0.50273	0.58724	0.65302	0.70535	0.52464	0.51132	0.50706
Probability.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table B.7.: EGARCH Model.Robust Standard Errors.

		Australia	Hong Kong	Japan	Malaysia	New Zealand	Singapore	South Korea	Taiwan	The Philippines
	Constant.	-0.963530***	0.000177	-0.984855***	-1.020333***	-0.954278***	-1.123588***	-1.005918***	-1.025048	-0.992066***
		[0.109301]	[0.003769]	[0.169434]	[0.374965]	[0.067041]	[0.086804]	[0.333197]	[2.627076]	[0.345785]
	ARCH term. (α_i)	-0.019535	-0.031853*	0.054537**	0.020523	-0.014552	-0.008746	0.007655	0.049452	0.028203
		[0.018402]	[0.019297]	[0.022653]	[0.038203]	[0.015891]	[0.023611]	[0.025730]	[0.066018]	[0.030595]
	GARCH term. (β_j)	0.900252***	0.999961***	0.900190***	0.899958***	0.899694***	0.899720***	0.899874***	0.899996***	0.899980***
		[0.011216]	[0.000057]	[0.016929]	[0.035545]	[0.006987]	[0.007727]	[0.033349]	[0.268370]	[0.034677]
	Assymetry term. (γ_i)	0.160482***	0.158387***	0.201732***	0.848944***	0.132210***	0.163514***	0.241308**	0.807913	0.812547***
		[0.030860]	[0.007080]	[0.039576]	[0.184853]	[0.029446]	[0.035654]	[0.055762]	[2.086076]	[0.211548]
t-value	Sign Bias.	0.9895	1.2382	0.1291	0.9561	0.05693	1.0734	0.4044	0.8319	1.586
	Negative Sign Bias.	0.1290	0.8716	1.0636	3.6091***	0.33667	0.7477	0.3594	3.3816***	4.045***
	Positive Sign Bias.	2.4490**	0.1222	1.5276	4.4063***	1.11104	0.9590	0.7363	3.9806***	6.037***
	Joint Effect.	6.4826*	1.7509	3.7874	32.9191***	1.67704	1.5445	0.7201	27.9911***	53.470***

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Table B.8.: R-vine.

Tree†	Edge‡	No.	Family	Parameter	Parameter2	Tau
1	1,5	2	t	0.79	7.06	0.59
	6,1	2	t	0.58	9.14	0.39
	6,2	2	t	0.20	9.80	0.13
	6,3	2	t	0.47	6.83	0.31
	6,4	17	SSB1	0.20	1.25	0.27
	6,8	17	SSB1	0.28	1.31	0.33
	6,7	2	t	0.52	6.06	0.35
	9,6	2	t	0.38	11.88	0.25
2	6,5|1	2	t	0.16	15.68	0.10
	7,1|6	2	t	0.11	7.88	0.07
	4,2|6	2	t	0.04	11.33	0.02
	4,3|6	5	F	-0.56	0.00	-0.06
	9,4|6	2	t	0.22	12.99	0.14
	7,8|6	2	t	0.31	8.41	0.20
	9,7|6	2	t	0.20	14.50	0.13
3	7,5|6,1	2	t	0.02	12.49	0.01
	9,1|7,6	2	t	-0.05	20.20	-0.03
	3,2|4,6	104	Tawn	1.14	0.16	0.04
	9,3|4,6	2	t	0.02	16.00	0.01
	7,4|9,6	2	t	0.15	11.43	0.09
	9,8|7,6	2	t	0.08	12.50	0.05
4	9,5|7,6,1	2	t	-0.04	22.87	-0.03
	4,1|9,7,6	134	Tawn270	-1.15	0.12	-0.03
	9,2|3,4,6	2	t	-0.00	18.64	-0.00
	7,3|9,4,6	2	t	-0.03	8.38	-0.02
	8,4|7,9,6	2	t	0.10	12.70	0.07
5	4,5|9,7,6,1	40	BB8-270	-1.15	-0.87	-0.04
	3,1|4,9,7,6	2	t	0.02	12.04	0.01
	7,2|9,4,3,6	2	t	0.00	13.93	0.00
	8,3|7,9,4,6	2	t	0.09	13.79	0.06
6	3,5|4,9,7,6,1	2	t	0.02	15.57	0.01
	2,1|3,4,9,7,6	104	Tawn	1.40	0.02	0.01
	8,2|7,9,4,3,6	4	G	1.02	0.00	0.02
7	2,5|3,4,9,7,6,1	2	t	0.01	15.13	0.01
	8,1|2,3,4,9,7,6	26	J90	-1.02	0.00	-0.01
8	8,5|2,3,4,9,7,6,1	2	t	0.00	17.78	0.00

† LogLik= 4224.24, AIC= -8310.48, BIC= -7903.75.

‡ 1: Australia, 2: Hong Kong, 3: Japan, 4: Malaysia, 5: New Zealand, 6: Singapore, 7: South Korea, 8: Taiwan, 9: The Philippines.

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