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Post-2008 short and long-term volatility transmission from the United States to the Asian Tigers – ICSS algorithm based robust quantile regression approach

Thesis Supervisor:

Dr. S. (Sjoerd) van den Hauwe

Candidate:

Dhr. A.W.C. (Alex Willem Cornelis) van Beek

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Statement of Originality

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Abstract

This thesis investigates the transmission of transitory and permanent parts of volatilities from the S&P500 futures market to three Asian Tiger futures markets - namely the Hang Seng futures market, the Kospi 200 futures market, and the Singapore MSCI 200 futures market by a two-step procedure. Firstly, transitory and permanent volatilities are estimated based on the optimal component GARCH model. Secondly, the estimated volatilities are embedded in the robust quantile regression. Moreover, a sub-sample analysis is performed, observing three opposite sub-samples; samples with low, moderate, and crisis levels of standard deviation, for the detection of structural breaks the modified Iterative Cumulative Sum of Squares algorithm. Overall, significant transitory and permanent volatility transmission effects are discovered for all three Asian Tigers futures markets. Both types of transmission effects decreased over time. This decrease is positive; the three futures markets became less dependent on the United States futures market. The permanent transmission effect is proven to be stronger than the transitory volatility transmission effect for all the three Asian Tigers futures markets.

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1   Introduction

Potential of upcoming markets

Under the ongoing (financial) globalization, global financial markets and economies are increasingly integrated due to increased international trade and increased free capital flow. Developed economies and also emerging markets became more internationalized and financially integrated with the global financial system in the last decades. An emerging market is a financial market with similar characteristics to a developed market but does not (yet) fully meet the standards of developed markets. Overall, these emerging markets are smaller, riskier, and more illiquid than developed markets. The integration and internalization of these emerging markets result from financial liberalization, deregulation, and structural changes in the national economies. According to Harvey (1993), investing in upcoming markets have at least three attractive qualities. Two of those qualities are their high average returns and their low correlation. Thereby, diversification into these markets should yield lower overall volatility and higher expected returns. Portfolio theory states that low correlation portfolios enhance the return-to-volatility ratio by shifting the mean-variance frontier to the left.

The Asian Tigers were considered emerging markets around the turn of the millennium by many investors, researchers, and regulators. The original tigers are: Hong Kong, Singapore, South Korea, and Taiwan, and experienced a remarkable record of high and sustained economic growth. The World Bank (1993) recognized this potential in a report stating that from 1965 to 1990, the twenty-three economies of East Asia grew faster than all other regions of the world. During this period, the Asian Tigers experienced rapid industrialization and experienced growth rates of more than 7 percent per annum, which is exceptionally high. The World Bank states that the Asian Tigers experienced this rapid growth due to neo-liberal-oriented policies during an economic boom period combined with an export-oriented view on trade, low taxes, and governments that preferred minimal welfare states. In the present times, the original Asian Tigers economies have developed themselves in high-income economies. Singapore and Hong Kong became significant financial hubs in the global financial system, while Taiwan and South Korea serve leadership roles in the manufacturing of electronic devices.

Research motivation

However, financial integration also comes with downsides. Given that Harvey's theories date from 1993, the premises might have changed over time. Chiang, Jeon, and Li (2007) applied a dynamic conditional-correlation model to nine Asian daily stock-return data series, which including all the Asian Tigers, from 1990 to 2008. They discovered that during the Asian crisis, from July 1997 through early 1998, Asian financial markets experienced a series of financial distresses, which rapidly spread and sequentially spread from one country to another country in a short interval of intense crises. The financial distress spread even further to Russia and Latin America. In the short-run, the damage of the crisis not only caused a plunge in asset prices across these Asian financial markets but also created capital flights and speculative runs. This lead to considerable instability of the financial system of the entire region. A long-term consequence of the crisis and its spillover effects was that investors experienced a dramatic loss of confidence in Asian markets. This loss of trust jeopardized the economic growth of the region.

Rightfully modelling these financial interrelationships and volatility transmission effects should interest not only policymakers but also investors. For policymakers, the results help draw up new financial regulations to decrease the risks associated with the financialization of global economies. For investors, besides gaining capital gains by investing in foreign markets, rightfully modeling volatility transmission effects could also be helpful in financial risk management.

Research question and hypothesis

This thesis investigates the extent of the short-term and the long-term volatility transmission processes from the United States futures market to the three Asian Tigers futures markets. Namely, the Hang

Seng futures markets, the Kospi 200 futures market, and the Singapore MSCI 200 futures market. For these futures contracts, reliable data is available, and all the futures contracts exhibited (high) volatility swings, making them exciting to model. The main hypothesis for this thesis is that the Asian Tigers are net receivers of both transitory (short-term) volatility shocks and permanent (long-term) volatility shocks originated from the United States.

Research methodology and results

In order to test this hypothesis, the following research methodology is applied. Firstly, the prices are converted to log-returns and scaled by a factor of 100. The applied scaling is for practical optimization reasons. Based on these returns, summary statistics are calculated and return plots are presented. Secondly, based on the newly defined returns, a component GARCH model is fitted with six different innovation distributions. Namely, three conventional ones and three unconventional and more complex ones. After the estimation of these different models employing information theory, the best fitting models are selected. After estimating the permanent volatilities components and transitory volatilities components, the best-fitting skewed densities in the robust quantile regression needs to be determined.

After determining the best fitting model based on the median, the robust quantile regression, with the best performing skewed distribution, is estimated again on the following quantiles: 0.05, 0.20, 0.35, 0.50, 0.65, 0.80, 0.95. Based on the obtained parameter values, there is a discussion on the results of the full-sample analysis. After the full-sample analysis, the sample is split up into sub-samples. In order to detect structural breaking points, the modified Iterative Cumulative Sum of Squares algorithm is applied to the return data of all four futures markets. Unfortunately, the modified ICSS algorithm returned to many structural breaking points to model all regimes. Therefore, the classification of the sub-sample periods, namely: samples with low, moderate, and crisis level of standard deviation, are based on the levels of standard deviation in prespecified date ranges. After the classification of the periods, the robust quantile regression is applied at the different sub-samples, and the results are discussed.

Overall, significant transitory and permanent volatility transmission effects are discovered for all three Asian Tigers futures markets. However, both types of transmission effects decreased over time. This decrease is positive; the three futures markets became less dependent on the United States futures market. In addition, the permanent transmission effect is stronger than the transitory volatility transmission effect for all the three Asian Tigers futures markets. These results confirm the hypothesis, although the level of volatility transmission seems to be decreasing.

Related literature and research contribution

The following results were obtained by existing academic research devoted examining of volatility transmission and correlation from international stock markets to Asia. In the existing literature, to investigate volatility transmission between international markets, three volatility models are considered—namely, GARCH models, regime-switching models, and stochastic volatility models.

However, the empirical evidence was found mixed and indecisive. Hamao Masulis, and Ng (1990) discovered volatility transmission effects from New York to Tokyo as a proxy for Asia, but Japan might not represent the Asian Tigers economies. Pan and Hsueh (1998) discovered contemporaneous unidirectional volatility and return spillover effects from the United States futures market to the Japanese futures market. Wang, Gunasekarage, Power, Fetherston, and Batten (2005) discovered return spillovers from the American market to Pakistan, India, and Sri Lanka and volatility spillovers from the US to the Indian market and the Sri Lankan market.

On the opposite side, Kaur (2004) discovered significant correlations between the United States stock markets and the Indian stock markets but they were time-specific. Ng (2000) did not discover significant volatility transmission effects from the United States to Japan. Bae and Andrew Karolyi (1994) concluded that the magnitude and persistence of return shocks originating in Tokyo or New

York that transmit to the other markets are significantly underestimated if leverage effects are ignored.

This research contributes to the existing literature base because it uses several innovative approaches, introduced by Živkov, Manić, and Đurašković (2020), which sheds new light on the dynamics of volatility transmission between the United States and Asian Tigers. Several earlier studies have already been devoted to the study of volatility transmission between those countries, but not a single article was found applying the techniques used in this thesis.

Recent events which emphasises relevance

Firstly, the example of the Asian Crisis serves as a perfect example that financial globalization offers potential and that it comes with increased co-integration and its downsides of financial markets. Therefore, information regarding one equity index's financial and economic fundamentals gets transmitted to other indices, thus affecting foreign stock markets. This flow of information, affecting other countries, is so-called volatility transmission. This increased co-movement amplifies the vulnerability of the global financial system's stability to short and long-term shocks.

Secondly, a more recent example is the global financial crisis which has again brought the interdependencies of international financial markets to the fore of research attention, according to Mun and Brooks (2012). Their results show that the majority of the correlations are more strongly explained by volatility rather than news. However, when the global financial crisis evolved, the role of news grew in importance.

The most recent example of the potential risks of financial globalization is the COVID-19 pandemic. So, Chu, and Chan (2021) compared the connectedness of stock returns in four recent financial crises. In the COVID-19 crash, in contrast to the first three crises, the market factors could not adequately explain the co-movement of returns during the COVID-19 outbreak, which leads to a substantial increase in the network connectedness in the financial networks in March and April 2020. This significant increase in the connectedness of the partial correlation networks implies an increase in systemic risk in the global financial system during the virus outbreak. According to Pukthuanthong and Roll (2009), a potential reason for the significant increase in the connectedness of the partial correlation networks is that the stock returns are integrated into the market factors and have small stock-specific volatility. Therefore, the unexpected downside risk may not be adequately explained by market factors during a financial crisis.

Research design limitations

The following limitations, furtherly explained in the conclusion section, arise due to the chosen research methodology. Firstly, using the data of a free data provider could lead to less reliable data. This issue could be resolved by extracting the data from a professional party. Secondly, the definition of volatility is abstract. Maybe the squared daily log-return is not a good proxy for real volatility. To resolve this issue, one could implement intra-day data instead of daily data. Thirdly, only one method of volatility modeling is considered. Namely, a component GARCH model with regimes there may be significantly better volatility modeling methods available and should be checked upon to increase the robustness of the results. Fourthly, in this thesis, only a single-order updating equation is used for the component GARCH model, although the auto-correlation functions show statistically significant information in higher lagged time-series values. Therefore, the precision of constructing the transitory part and permanent part of volatility may be improved by a higher-order updating equation. Fifthly, applying a fixed estimation method might not yield the best and most up-to-date results. Therefore, rolling window estimation methods may provide the researcher with more meaningful results. Lastly, the frequentist method is applied; it would be interesting to use an alternative approach. One alternative approach is the Bayesian estimation approach, which does allow for prior beliefs. It would be interesting to study if this alternative estimation method improves the precision of constructing the transitory part and the permanent part of volatility.

2 Literature review

Financial globalization made global financial markets and economies more correlated because of increased international trade and increased free capital flows. This increased correlation leads to information regarding the financial and economic fundamentals of one equity index getting transmitted to other indices, thus affecting foreign stock markets. However, there are different views and mixed results on how correlation, so volatility transmission effects, change over time.

Several academic studies have already been devoted to examining volatility transmission and correlation across international stock markets. In the existing literature, in order to investigate volatility transmission between international markets, three volatility models are considered—namely, GARCH models, regime-switching models, and stochastic volatility models. Below several references are given to papers applying one of these models in order to study volatility transmission. However, the empirical evidence was found mixed.

2.1 Literature on GARCH models

Firstly, the basic model for volatility modeling is the ARCH model by Engle (1982) and the Generalized version, GARCH, by Bollerslev (1987) has been applied to study relations between financial markets. The first study that applied univariate GARCH methodology to analyze relations between international markets was the study by Hamao et al. (1990). This study analyzes daily volatility transmission among the New York, London, and Tokyo stock markets using a multi-stage approach. The following methodology was applied in the study by Hamao et al. (1990):

1. For each market, a univariate GARCH(1,1) model is estimated by maximum likelihood;
2. The squared model residuals are applied as a regressor in the variance equation of the other financial market;
3. Based on the regression output, the existence of a significant relationship between market variance and volatility surprises of foreign markets can be determined.

Significant positive coefficients were discovered from New York to London and Tokyo and from London to Tokyo, indicating volatility spillovers. This study, interestingly, already indicates volatility transmission from United States markets to Asian markets.

Kanas (1998) studied volatility spillovers across the three largest stock markets of Europe by applying a univariate modified GARCH model, namely the EGARCH model allowing for leverage effects. Reciprocal spillover effects are discovered between Paris and London, between Frankfurt and Paris, and unidirectional spillover effects from London to Frankfurt. Furthermore, the research results show that spillover effects are asymmetric because negative news in one European stock market has a more significant effect on volatility than a positive shock with the same magnitude.

Pan and Hsueh (1998) studied the volatility transmission of stock returns between United States futures markets and Japanese futures markets. Daily opening and closing futures prices, to deal with the time difference, on the S&P 500 index and the Nikkei 225 index from 03-01-1989 up until 30-12-1993 were used. By applying a two-step univariate GARCH model, it was discovered that there are significant contemporaneous unidirectional volatility effects and return spill-over effects from the United States futures market to the Japanese futures market.

The aforementioned univariate model relates the conditional variance of the time series X as an explanatory variable for the conditional variance of series Y. However, this estimation method ignores the possibility of reversed causality in both directions. Moreover, it is not exploiting the co-variance between both time series. For these reasons, a multivariate GARCH model is preferred, which was first introduced by Engle, Granger, and Kraft (1984). The theoretical properties of multivariate GARCH models were established in the study by Engle and Kroner (1995).

Kaur (2004) investigated return and volatility spillover effects between two Indian stock markets, the Nifty and the Sensex, and between two stock markets from the United States, the S&P500 and the NASDAQ. The empirical results showed mixed evidence of volatility and return spillover effects between the stock markets of the United States and the Indian stock markets. Significant correlations between the US stock markets and the Indian stock markets were discovered but time-specific.

Ng (2000) studied the magnitude and changing dynamics of volatility and return spill-over effects from the United States and Japan to Pacific-Basin markets by applying a bi-variate GARCH volatility model. Significant spill-over effects were discovered from both the United States market and the Japanese market to Taiwan, Thailand, Singapore, and Malaysia. However, no significant volatility transmission effects were discovered from the United States to Japan.

Mukherjee and Mishra (2010) studied volatility and return spillover effects among the stock market of India with 12 other emerging and developed Asian stock markets by applying a multivariate GARCH model. For the analysis, both daily opening prices and closing prices from November 1997 until April 2008 are examined. The empirical results show that Korea, Singapore, Hong Kong, and Thailand are markets from where there is significant information flow in India. Moreover, the stock market of Pakistan and the stock market of Sri Lanka are discovered to be strongly influenced by movements, volatility swings in the Indian stock market.

Bae and Andrew Karolyi (1994) studied the joint dynamics of daytime and overnight return volatility for the Nikkei in Tokyo and the S&P500 in New York over 1988-1992. The analysis extended the multivariate GARCH framework to allow for asymmetric effects of positive and negative foreign market return shocks. They concluded that the magnitude and persistence of return shocks originating in Tokyo or New York that transmit to the other markets are significantly underestimated if leverage effects are ignored.

For the study of short and long-term volatility transmission from index futures of the United States to Asian Tiger index futures after the Global Financial crisis at different quantiles, no academic paper is found which exactly answers this research question applying a GARCH model.

The most closely related paper to investigate the research question, which studied Asian markets, is the paper by Wang et al. (2005). They studied return and volatility spillovers from the US and Japanese stock markets to three South-Asian capital markets. Namely, the Karachi Stock Exchange, the Colombo Stock Exchange, and the Bombay Stock Exchange. They construct a univariate EGARCH volatility spillover model, modeling for leverage effects, that allows the unexpected return of a South-Asian market to be driven by a local shock, a regional shock from Japan, and a global shock from the USA. The study discovered the following. Firstly, return spillovers in all three markets. Secondly, volatility spillovers from the US market to India and Sri Lankan markets and from the Japanese market to the Pakistani market. Thirdly, regional factors influence these three markets before the Asian financial crisis, but the global factor becomes more important in the post-crisis period. Although different financial products and markets were considered the same methodology, an EGARCH model could be applied. However, such a model would not say anything about the transitory part of volatility and the permanent part of volatility. Moreover, this research did not consider shocks at different quantiles.

2.2   Literature on regime-switching models

The second methodology to investigate volatility transmission is by regime-switching models. Several studies Hamilton and Susmel (1994), Edwards and Susmel (2001), Lamoureux and Lastrapes (1990), have been devoted to modeling volatility transmission by regime-switching methods. These papers all suggest that an almost integrated volatility behavior could be due to the possible existence of structural changes. By this logic Hamilton and Susmel (1994) and Cai (1994), introduced regime changing ARCH models. In these regime-changing ARCH models, the model parameters switch according to

a predetermined state or a regime matrix of the variable in the previous period. Thus, a non-linear regime switching ARCH model allows the behavior of the modeled time-series to depend on the state of the system. Gray (1996) extended the ARCH methodology to regime-switching GARCH models.

However, several studies, including Messow and Krämer (2013), show that structural changes in stochastic volatility models induce spurious persistence. Spurious persistence means that implied persistence does not tend to unity with the given size of the structural change and increasing sample size. Thus, no tendency to unity could be problematic when applying regime-switching models resulting in volatility being underestimated in high volatility states and overestimated in low volatility states.

On the other hand, the studies by Longin and Solnik (2001) and Ang and Chen (2002) serve as evidence that correlations are more prominent in magnitude when markets move downwards than the correlations when markets move upwards. In other words, market correlations are asymmetric, which is especially true for extreme market downside movements. Ang and Bekaert (2002) conclude that asymmetric correlations are not well captured by standard asymmetric, allowing for leverage effects, GARCH models, but a regime-switching model can capture asymmetries.

In practice, the following strategy is generally applied for regime-switching models:

1. Analyzing the time-series in order to detect possible changes in regime(s);
2. Modelling the time- series with a linear process and obtain the residuals;
3. Applying a test designed to detect non-linearity;
4. If non-linearity is discovered, deciding the best way to model this;
5. Model estimation, check for significant coefficients, and better fit relative to the linear model.

Based on the results obtained from different empirical studies analyzed, Soriano and Climent (2005) concluded that variances, co-variances, and correlations seem to change in time and state. Moreover, most of the studies show that high volatility states typically have a short length.

No study was discovered that studied short-and long-term volatility transmission from the United States index futures to Asian Tiger index futures after the Global Financial crisis at different quantiles by regime-switching models. The most closely related paper to investigate the research question, which studied Asian markets, by a regime-switching model is the study by Gallo and Otranto (2008). They studied the transmission mechanisms of volatility between five Asian markets by a new Markov Switching bi-variate model where the state on one variable feeds into the transition probability of the state of the other. Several model restrictions and hypotheses are tested to stress the role of one market relative to other markets. These tests are namely: spillover interdependence, co-movement, independence, and Granger non-causality. The Markov Switching bi-variate model is estimated on the weekly high-low range of five Asian financial markets, assuming a central role for the financial market of Hong Kong. The study results show plausible market characterizations in the long run with volatility spillover effects from Hong Kong to Korea and Thailand. Moreover, interdependence between Hong Kong and Malaysia is discovered and co-movement between Hong Kong and Singapore.

2.3   Literature on stochastic volatility models

The last methodology on volatility transmission discussed is Stochastic Volatility (SV). The most basic stochastic volatility models introduced by Taylor (1982) considered volatility as a variable that could not be observed and models the logarithm of volatility as a stochastic linear model. Commonly, the logarithm of volatility is modeled by an autoregressive process. The main advantages of Stochastic Volatility over GARCH models are: generalization to the multivariate case is much easier, and properties of the series being analyzed can be easily obtained. However, SV models have not been as popular in academics as GARCH models, as is suggested by the few empirical studies existing. The lack of academic literature is also why in this thesis, the most references are studies that examined GARCH volatility models instead of regime-switching volatility models or stochastic volatility models.

Savva, Osborn, and Gill (2005) examined, by employing a bivariate VAR model, the price spillover effects, the volatility spillover effects, and correlations between the daily prices of the American S&P500, the British FTSE-100, the German DAX-30, the French CAC-40, the Italian MIBTEL-30, and the Spanish IBEX-35 from 03-08-1990 to 12-04-2006. The empirical results show a strong and significant co-integration relation between the United States stock market and the European stock markets. Furthermore, the results indicate volatility spillover effects from the United States stock market to the European stock markets and volatility spillover effects from the European stock markets to the stock market of the United States.

Once again, no study was discovered which answered the exact research question by applying stochastic volatility models in the Asian stock markets. The most closely related paper is the paper by Yarovaya, Brzeszczyński, and Lau (2016). They studied the channels of volatility transmission across stock index futures in 6 major developed and emerging markets in Asia based on forecast error variance decomposition from a vector autoregressive (VAR) model. It is analyzed whether common volatility spillovers tests are susceptible to the choice of range volatility estimators. Their results demonstrate strong relations between markets within the Asian region, indicating that the signal receiving markets are sensitive to negative and positive volatility shocks. This increased shock sensitivity reveals the asymmetric nature of volatility transmission channels. Moreover, it is discovered that some markets play a destabilizing role while others - contrary to popular belief - have a stabilizing effect on other Asian markets

2.4   Research implications

To sum up the referred literature, overall, the results of the referred studies are indecisive if significant volatility spillover effects from the United States to Asia exist. Hamao et al. (1990) discovered volatility transmission effects from New York to Tokyo as a proxy for Asia, but might not be representative for the Asian Tigers economies. Pan and Hsueh (1998) discovered contemporaneous unidirectional volatility and return spillover effects from the United States futures market to the Japanese futures market. Wang et al. (2005) discovered return spillovers from the American market to the markets of Pakistan, India, and Sri Lanka and volatility spillovers from the US to the Indian market and the Sri Lankan market. On the opposite side, Kaur (2004) discovered significant correlations between the United States stock markets and the Indian stock markets but they were time-specific. Ng (2000) did not discover significant volatility transmission effects from the United States to Japan. Bae and Andrew Karolyi (1994) concluded that the magnitude and persistence of return shocks originating in Tokyo or New York that transmit to the other market are significantly underestimated if leverage effects are ignored.

This literature review shows, like aforementioned, that the empirical results of the various academic papers have been inconclusive on whether significant volatility spillover effects from the United States to Asia exist. This thesis addresses empirical results related to volatility transmission from the United States to Asia to bring some new evidence to this discord. Namely the Asian Tigers. In order to answer this question, the paper by Živkov et al. (2020) is used as the anchor point for the methodology.

The paper uses GARCH models and regime-switching methods to model volatility transmission in the short and long run. Živkovs paper does not concern (Asian) financial markets but permanent and transitory spillover effects from Brent oil futures to four agricultural futures. Namely, corn, wheat, soybean, and canola. The construction of the permanent and transitory volatility parts is done via a component GARCH model, considering six different distribution functions. The constructed volatility time series, with a transitory and a permanent volatility part, are then embedded in the robust quantile regression framework. After estimating the transitory and permanent volatility for the whole data-set, Živkov applies a modified Iterative Cumulative Sum of Squares (ICSS) algorithm to create three different regimes to investigate the transmission effects in calm periods and crisis periods.

3   Methodology

This thesis aims to determine the development of the permanent and transitory volatility spillover effects from the United States financial market to Asian financial markets. The whole methodology is in accord with the paper by Živkov et al. (2020).

3.1   Component GARCH model

For the estimation of the component GARCH models, the R package "rugarch" by Ghalanos (2014) is used. This package is open-source software for univariate GARCH modeling. For the fitting of component GARCH models and parameter estimations, the augmented Lagrangian solver by Ye (1997) is used implemented in R by Ghalanos and Theussl (2013).

Augmented Lagrangian methods are a specific algorithm class for solving constrained optimization problems. Further theoretical background on Augmented Lagrangian methods is given by Ye (1997). In this thesis, the constrained optimization problem is the minimization of the conditional log-likelihood of the fitted models and their parameters. The GARCH dynamics and conditional likelihood calculations, essential for this thesis, are done in C for speed.

In order to decompose the conditional volatility of the time-series into permanent effects and transitory effects, a component GARCH model developed by Lee and Engle (1993) is applied. The main reason for this split is, by segmenting total conditional volatility into a transitory volatility part and a permanent volatility part, it becomes possible to assess the nature of short-run volatility relation, which influenced by market and investor behavior and sentiments, and the extent of the long-run connection, caused by fundamental factors.

The conditional mean model is given in formula 1, the long-run GARCH component of the conditional variance is described by formula 2, and the full conditional volatility GARCH model is given by formula 3.

$$r_t = \mu + \phi_1 r_{t-1} + \epsilon_t, \quad \epsilon_t \overset{\text{i.i.d.}}{\sim} (0, \sigma_t^2) \tag{1}$$

Where in the conditional mean model, formula 1, the symbols are representing the following. $r_{i,t} = 100 * \log P_{i,t}/P_{i,t-1}$ is the log-returns of the financial asset, $r_{i,t-1}$ is the lagged log-return, μ is the constant term, ϕ_1 is the AR term, ϵ_t are independently and identically distributed error terms of the selected financial assets, and σ_t^2 denotes the conditional variance. Further, information on the construction of the error terms is given in the next paragraph. The conditional mean equation in formula 1, is a autoregressive process of order 1 with a constant term μ. An AR(1) process is assumed to overcome auto-correlation bias.

The ϵ_t term, are the model residuals. Residuals are estimates of the model error calculated by subtracting the observed value from the predicted model value. The predicted value is calculated from the chosen model, after all the model parameters have been estimated from the in-sample data-set. Carefully examination of model residuals is one of the most important parts of statistical modelling. This is especially true for (component) GARCH modeling of the volatility of a time-series, as the ϵ_t term serves as model component in the volatility model. Moreover, the residuals tells if the model assumptions are reasonable and if chosen model form is appropriate. This means that, in general, rightfully modelling the innovation distribution leads to statistically more meaningful parameters estimations increasing the reliability of the study results.

Therefore, to model the permanent and transitory effects of volatility as accurately as possible, six different innovation distributions of $\epsilon_t \overset{\text{i.i.d.}}{\sim} (0, \sigma_t^2)$ are considered. Firstly, three traditional innovation distribution are considered. Namely, the normal distribution $\epsilon \sim N(0, h_t)$, the Student's t-distribution $\epsilon \sim S_t(0, h_t, \nu)$, and the generalized error distribution $\epsilon \sim GED(0, h_t, \nu)$. Secondly, three unconventional and more complex heavy tailed, so more able to model leptokurtosis, are studied. Namely, the

normal inverse Gaussian distribution $\epsilon \sim NIG(0, h_t, \nu, \kappa)$ by Barndorff-Nielsen (1997), the generalized hyperbolic distribution $\epsilon \sim GHYP(0, h_t, \nu, \kappa)$ by Barndorff-Nielsen (1997), and the Johnson SU distribution $\epsilon \sim JSU(0, h_t, \nu, \kappa)$ by Johnson (1949). The symbols ν and κ represent the shape and skewness parameters respectively, of which presents is confirmed in table 2.

$$q_t = \omega + \eta_1(q_{r-1} - \omega) + \eta_2(\epsilon_t^2 - \sigma_t^2) \tag{2}$$

Where in the long-run GARCH component of the conditional variance, formula 2, the symbols are representing the following. q_t represents the long-run component of the conditional variance, reflecting shocks to economic fundamentals and is describing the long-run persistent behavior of the conditional variance. q_t converges to the permanent component intercept, ω, with a magnitude of η_1, the permanent component autoregressive term. The coefficient η_2, the permanent shock term, indicates how shocks affect the permanent component of volatility. The closer the parameter η_1 is to one, the slower q_t approaches ω, and the closer it is zero, the faster it approaches ω. So, the parameter η_1 gauges the long-run persistence. The coefficient η_2 indicates how shocks affect the permanent component of volatility.

$$\sigma_t^2 = q_t + \alpha_1(\epsilon_{t-1}^2 - q_{t-1}) + \beta_1(\sigma_{t-1}^2 - q_{t-1}) \tag{3}$$

Where in the full conditional volatility GARCH model, formula 3, σ_t^2 denotes the conditional variance, q_t represents the long-run component of the conditional variance derived from formula 2, $_1$ represents the transitory component ARCH term, and β_1 represents the transitory GARCH term. The term of the coefficient α_1, $(\epsilon_{t-1}^2 - q_{t-1})$, measures the initial impact of a shock to the transitory component. The term of the coefficient β_1, $(\sigma_{t-1}^2 - q_{t-1})$, indicates to the short-run component and represent the degree of memory in the transitory state.

The component GARCH model is stable if the autoregressive coefficient, η_1, of permanent volatility exceeds the coefficients $(\alpha_1 + \beta_1)$ in the transitory component, implying that short-run volatility converges faster than the long-run volatility.

The component GARCH model is estimated with the six-difference innovation distributions. Based on the average of the following measures from information theory, the best fitting model is selected: the Akaike Information Criterion (AIC) by Akaike (1974) given in formula 4, the Bayesian Information Criterion (BIC) by Schwarz (1978) given in formula 5, and the Hannan-Quinn Information Criterion (HQIC) by Hannan and Quinn (1979) given in formula 6. The definitions are from Ghalanos (2014).

$$AIC = \frac{-2LL}{N} + \frac{2m}{N} \tag{4}$$

$$BIC = \frac{-2LL}{N} + \frac{m \log_e(N)}{N} \tag{5}$$

$$HQIC = \frac{-2LL}{N} + \frac{(2m \log_e(\log_e(N)))}{N} \tag{6}$$

LL is the log-likelihood, m is the number of parameters, and N is the number of observations. Taking the mean of several information criteria is the preferred method because the permanent and transitory spill-over effects of volatilities are modeled as accurately as possible. After selecting the best-performing model, this model will be used for the robust quantile regression. Using the average of three information criteria is a addition to Živkov et al. (2020), which only use the AIC criterion.

3.2   Robust quantile regression

For the estimation of the robust quantile regression the R package "lqr" by Galarza, Benites, Bourguignon, and Lachos (2021) is used. This package fits a robust linear quantile regression model using a new family of zero-quantile distributions for the error term. Namely, the normal distribution, the Student's t-distribution, the Laplace distribution, the Slash distribution, and the contaminated normal distribution. According to Galarza, Lachos, Cabral, and Castro (2017), the widely popular mean

regression, such as the Ordinary Least Squares (OLS) regression method, could be inadequate if the probability distribution of the observed responses does not follow a symmetric probability distribution. The quantile regression model is preferred over a mean regression model to deal with asymmetric probability distributions. The quantile regression model turns out to be a more robust alternative for dealing with outliers and the misspecification of the error distribution because it can characterize the entire conditional distribution of the outcome variable.

Due to time differences and different opening hours of the financial markets, the daily prices originated from New York need to be matched with the daily prices in Asia. This time matching is correspondence with a paper by Pan and Hsuch (1998), investigating the nature of volatility transmission between the U.S. and Japanese futures markets. Therefore, in table 1 the time differences and different opening times are given.

City	Time difference NY	Opening time	Closing time	NY opening time	NY closing time
Hong Kong	+12	09:00	16:00	21:00	04:00
Seoul	+13	09:00	15:30	22:00	04:30
Singapore	+12	13:00	17:00	01:00	05:00
New York	0	09:30	16:00	09:30	16:00

Table 1: Time differences between New York City and the Asian Tigers capital cities. One thing to keep in mind that the NY closing time of New York is a day earlier than the NY opening time of the Asian Tigers.

The standard robust quantile regression formula takes the conditional quantile function of y at quantile τ, given regressor x, and some form of distribution function F_u of the errors. Due to the time differences, the standard robust quantile regression formula will be run with a lagged time-series component. The final equation is given below:

$$Q_y(\tau|x) = \beta_1 + \beta_2 x_{t-1} + F_u^{-1}(\tau) \tag{7}$$

Where parameter y stands for the permanent or the transitory component of the Asian Tiger futures volatility of the daily **opening** price and parameter x denotes the permanent or the transitory component of the S&P500 future volatility of the daily **closing** price. β_2 is the parameter of interest and models the magnitude of a shock in the volatility of the United States to the Asian Tigers.

For the different distributions the regression in formula 7 is run at $\tau = 0.50$. Based again on the mean of the formulas from information theory, in the formulas 4, 5, and 6, the best performing model is selected. After selecting the best performing model and skewed distribution, the robust quantile regression in formula 7 is performed at the following quantiles: 0.05, 0.20, 0.35, 0.50, 0.65, 0.80, 0.95. These results will be plotted and discussed in the full-sample analysis section.

3.3   Modified Iterative Cumulative Sum of Squares (ICSS) algorithm

In order to investigate if, given the relatively long time-span volatility transmission processes have developed over time, the sample, which indicates periods of market tranquility and turbulence, will be sub-sampled in this subsection. The sub-samples will be constructed by testing for structural breaks in the variance of the return data of the futures contracts, and each period in between a structural break and a new structural break will be classified as a sub-sample. For each classified sub-sample, the robust quantile regression is run, and the results are discussed upon in the robustness check section. These results can be important for investors and their investment decisions and regulators and their policies as it gives crucial information on volatility transmissions during different market conditions.

Iterative Cumulative Sum of Squares (ICSS) algorithms makes it possible to detect multiple variance changes in a sequence of independently distributed observations. Financial time series often do not follow the usual statistical assumption of constant variance required for most econometric time-series models. Instead, these time-series behave stationary for some time, but the error term's variance is often time-dependent. After that, the time series stays constant at this new level of variance until

another structural break occurs. According to Inclan and Tiao (1994), the main point of applying an ICSS algorithm is to study the variance of a given sequence of time-series observations retrospectively, so all information on the time-series is used to indicate points of variance change.

For the construction of the exact breaking points between the sub-samples, a modified version of the iterative cumulative sum of squares (ICSS) algorithm, originally from Inclan and Tiao (1994), by Sansó, Aragó, and Carrion-i-Silvestre (2003) is applied in GAUSS. Clower (2018) gives a simple test for structural breaks in variance algorithm.

The main advantage of Sansó et al. (2003) ICSS version over Inclan and Tiao (1994) ICSS version, according to Živkov et al. (2020), is that it resolves the issue of oversized break detection, which is considered an intrinsic future of a basic ICSS algorithm. Expressly, the modified ICSS, according to Živkov et al. (2020), can recognize the fourth-moment properties of a time series explicitly. Moreover, it assumes that data is independently and identically distributed with mean zero and a constant variance. Mathematically stated, $y_t \overset{\text{i.i.d.}}{\sim} (0, \sigma_t^2)$.

Applying a non-parametric adjustment based on Bartlett kernel, the modified Iterative Cumulative Sum of Squares algorithm is defined as follows:

$$modified\ ICSS = \sup_{k} \left| T^{-0.50} G_k \right|, \tag{8}$$

$G_k = \hat{\lambda}^{-0.50}[C_k - (k/T)C_T]$, $\hat{\lambda} = \hat{\gamma}_0 + 2 * \sum_{l=1}^{m}[1 - l(m+1)^{-1}]\hat{\gamma}_l$, $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(\tau_t^2 - \hat{\sigma}^2)(\tau_{t-1}^2 - \hat{\sigma}^2)$, and $\hat{\sigma}^2 = T^{-1}C_T$. Following the procedure of Newey and West (1994), the lag truncation parameter is set to be the value $m = 0.75T^{1/3}$. The asymptotic distribution of the modified ICSS test statistics, under general conditions, is given by $\sup_l |W^*(l)|$, and the 95th percentile critical value for the asymptotic distribution of the modified ICSS statistic is 1.4058.

4 Data

This thesis uses the daily futures prices of the indices of the SP500, the Hang Seng, the Kospi 200, and the Singapore MSCI 200 from 11th of November 2009 up until the 4th of April 2021. Futures prices of the selected assets are considered over spot prices because futures prices, by definition, incorporate all available information. Thus can provide a more realistic volatility spill-over effect measurement in comparison with the spot prices. Below the price development plots are given for the date range:
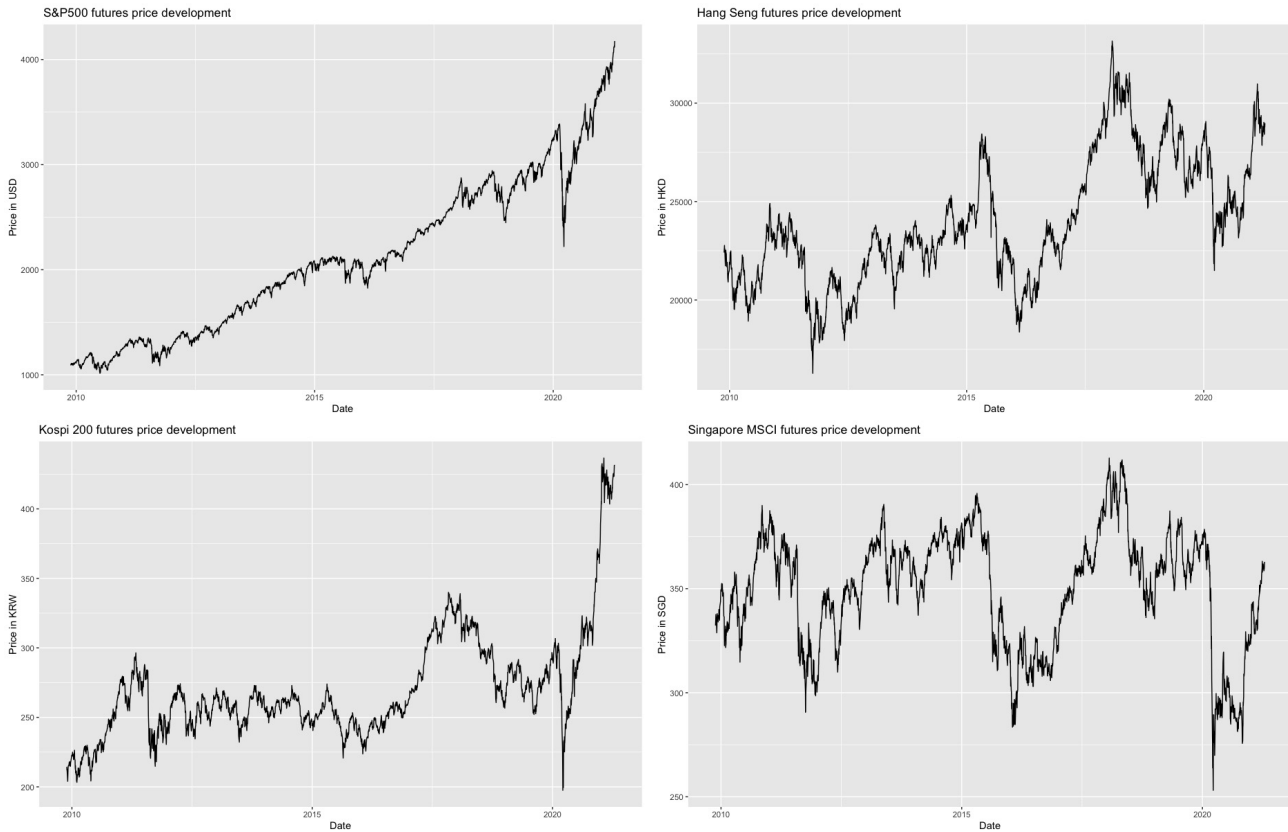

Figure 1: Price dynamics of the futures contracts ranging from 19th of November 2009 up until 16th of April 2021. The S&P500 future price is in United States Dollars per contract; the Hang Seng future price is in Hong Kong Dollars per contract; the Kospi 200 future price is in South-Korean Wong; the Singapore MSCI future price is in Singapore Dollars.

The 11th of November 2009 until the 4th of April 2021 was the maximum date range for the futures. Therefore, implemented. This date range should be sufficient to answer how after the most profound effects of the Global Financial Crisis of 2008, volatility spillover effects developed after this event. The Asian Tiger Taiwan is excluded from this thesis because limited futures data was available. The data is extracted from www.investing.com, which is in correspondence with Živkov et al. (2020). All observed futures are expiring contracts.

The log-return of the different futures is defined as: $r_{i,t} = 100 * \log P_{i,t}/P_{i,t-1}$, scaling by 100 is applied for optimization reasons. Firstly, the observations in summary table 2 are obtained from all data available in the date range. Secondly, to model volatility spill-overs more accurately, all futures contracts are individually merged and synchronized with the S&P500 index on date.

Table 2: Summary statics of the different futures contracts.

Future/measure	N	Mean	SD	Skewness	Kurtosis	Robust skewness	Robust kurtosis	LB(Q^2)	DF-GLS
S&P500	2844	0.0471	1.1006	-0.9654	15.1546	0.0402	-0.8813	0.0000	-8.2838
Hang Seng	2740	0.0092	1.2528	-0.3742	2.7318	-0.0109	-0.5262	0.0000	-8.6720
Kospi 200	2721	0.0258	1.1564	-0.1142	6.6779	0.0005	-0.6103	0.0000	-8.9547
Singapore MSCI 200	2832	0.0033	0.9723	-0.288	5.1056	0.0017	-0.5279	0.0000	-7.2917

Notes: LB(Q^2) test presents p-values of Ljung-Box Q-statistic of the squared residuals for 20 lags. DF-GLS is Dickey-Fuller generalized least squares test with 10 lags assuming only constant, and the 1% and 5% critical test values are -2.566 and -1.941, respectively.

Robust skewness, formula 9, and robust kurtosis, formula 10, are quantile-based rather than on averages. Measures based on quantiles rather than averages might be preferred because average-based measures are sensitive to outliers in the observed time series, which could corrupt the research findings.

$$SK_R = \frac{Q_3 + Q_1 - 2 * Q_2}{Q_3 - Q_1} \tag{9}$$

$$KR_R = \frac{Q_4 + Q_0}{Q_3 - Q_1} \tag{10}$$

Where the quantiles are defined as: $Q_0 = \tau^{0.025}, Q_1 = \tau^{0.25}, Q_2 = \tau^{0.5}, Q_3 = \tau^{0.75}, Q_4 = \tau^{0.95}$.

The summary table, table 2, indicates a daily positive mean return of approximately zero for all futures with the highest return on the S&P500 future and the lowest return for the Singapore MSCI 200 future. Due to the fact that the average daily return is approximately zero, volatility can be defined as $\sigma_t^2 = r_t^2$ instead of $\sigma_t^2 = (r_t^2 - \mu)$, this phenomenon is known in the financial sector as mean-blur.

The standard deviation of the scaled log-returns indicates the following order of riskiness from high to low: the Hang Seng future; the Kospi 200 future; the S&P500 future; the Singapore MSCI 200 future.

Based on the skewness and the kurtosis, non-normality could be concluded by the negative skewness and high (lepto-)kurtosis. All futures are fat-tailed and left-asymmetric in comparison to the Gaussian distribution. The level of non-normality decreases by applying robust measures based on quantiles rather than averages.

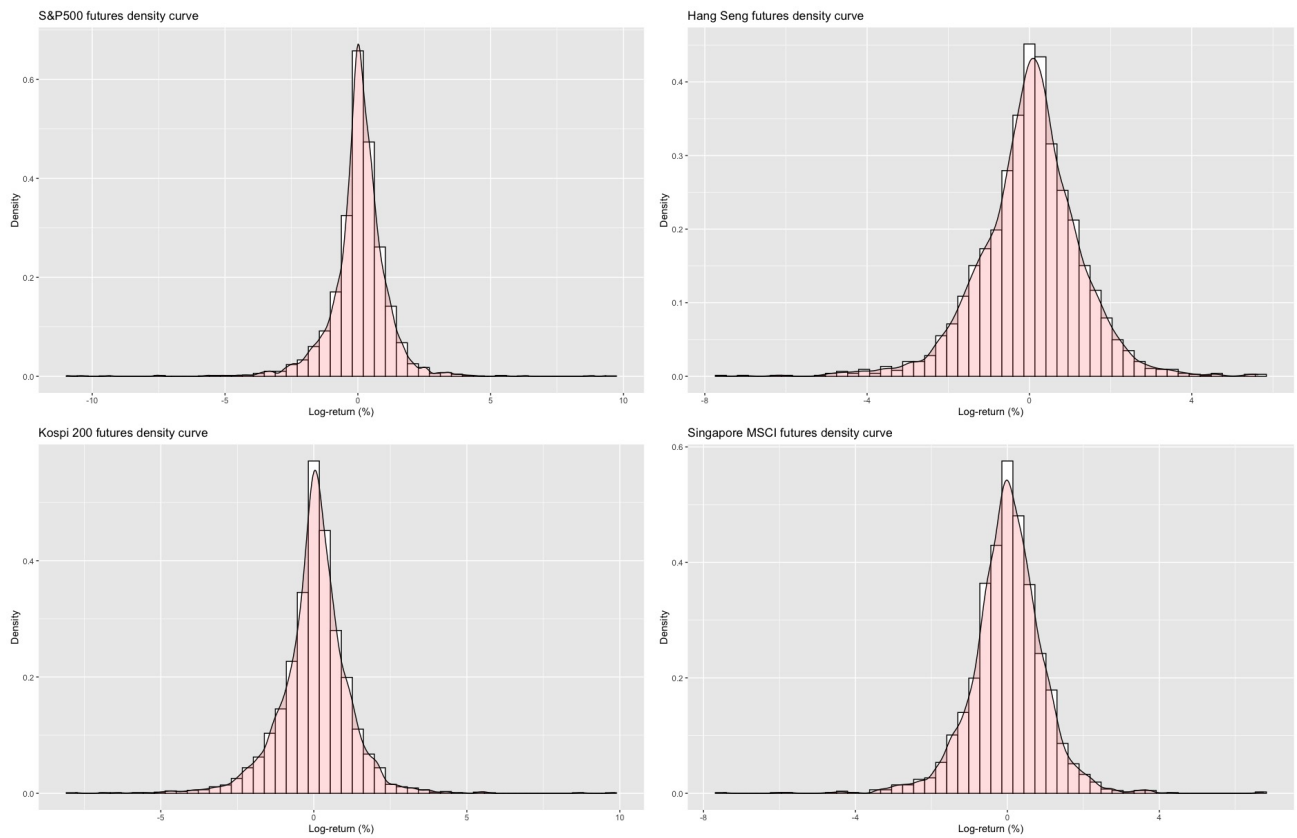In order to visualize the futures return densities, in figure 2 the density plots are given.

Figure 2: Return density plots of the log-returns of the different futures indices.

Based on figure 2, fatter tails and higher peakness, (lepto-)kurtosis, could be observed for all the futures log-returns. Therefore, it seems reasonable to conclude that distributions that capture these characteristics outperform distribution which do not.

In order to visualize auto-correlation in the squared log-returns, ACF-plots are given in figure 3.
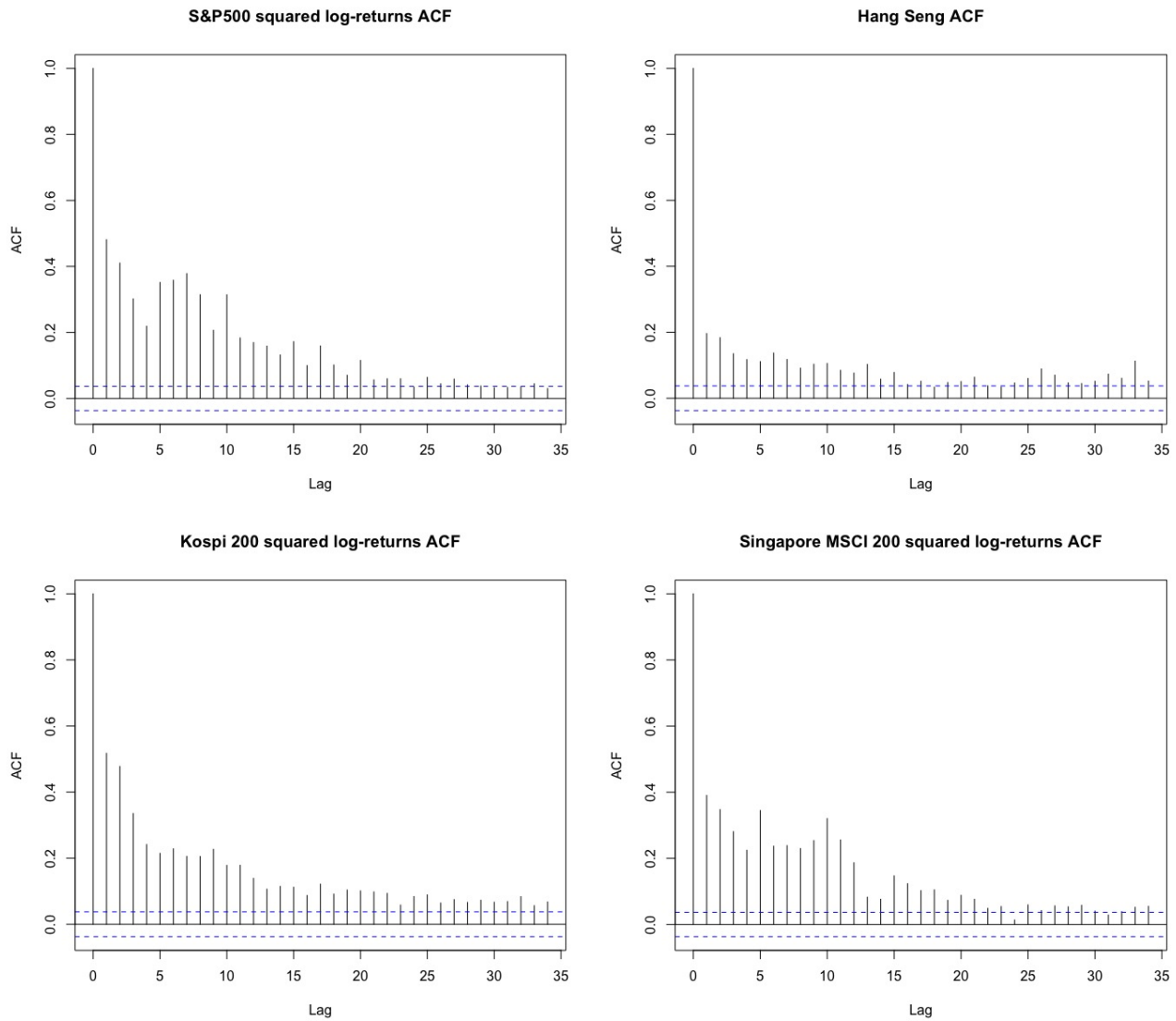

Figure 3: Auto-correlation plot of the squared log-returns of the different futures indices.

Based on figure 3 it is possible to conclude that at the first lags, there is statistically significant information for current values, so the plots confirm the result of the Ljung–Box test. The Ljung–Box test is a type of statistical test of whether any of a group of auto-correlations of a time-series are different from zero, introduced by Box and Pierce (1970). For constructing predictive volatility models, significant auto-correlation is desirable in the squared log-returns. All probability values of the Ljung–Box test indicates rejection of the null hypothesis: the data is independently distributed. Therefore, the LB(Q^2) test statistic suggested auto-correlation in the empirical time series. Thereby, it becomes possible to apply component GARCH models for volatility modeling.

The DF-GLS test for a unit root has been developed by Elliott, Rothenberg, and Stock (1996) and test for an autoregressive unit root in the detrended series. For volatility modeling, the volatility time-series, as proxy r_t^2 is used, need to be stationary. The DF-GLS test suggests that all squared returns are stationary.

5   Results

5.1   Component GARCH model estimation

In order to model the transitory part of volatility and the permanent part of volatility for every selected future as accurately as possible, the component GARCH model is estimated with six different innovation distribution functions. Namely, the normal distribution (Normal), the Student's t-distribution (Std), the generalized error distribution (GED), the normal inverse Gaussian distribution (NIG), the generalized hyperbolic distribution (GHYP), and the Johnson SU distribution (JSU). Below, in table 3, the mean of the measures in the formulas 4, 5, and 6, and its relative likelihood are given for the different innovation distributions.

	S&P500		Hang Seng		Kospi 200		Singapore MSCI 200	
	Mean	RL	Mean	RL	Mean	RL	Mean	RL
Normal	2.5286	0.9480	3.1778	0.9764	2.8607	0.9687	2.5598	0.9849
Std	2.4425	0.9896	3.1357	0.9972	2.8162	0.9905	2.5340	0.9977
GED	2.4445	0.9905	3.1320	0.9990	2.8003	0.9985	2.5368	0.9963
NIG	2.4235	1	3.1306	0.9998	2.8021	0.9976	2.5293	1
GHYP	2.4243	0.9996	3.1300	1	2.7972	1	2.5306	0.9994
JSU	2.4244	0.9996	3.1313	0.9996	2.8057	0.9958	2.5294	1

Table 3: Information measure and relative likelihood (RL) values for the different innovation distributions of the component GARCH model. RL is defined as $RL = e^{(AIC_0 - AIC_{NO})/2}$. AIC_0 is the optimal AIC, while AIC_{NO} denotes all non-optimal AIC values.

The model with the lowest mean is the best performing distribution, while the relative likelihood shows how the distribution is performing relative to the optimal distribution. Based on results in table 3 it is possible to conclude that for all the future contracts, a non-traditional innovation distribution outperforms the standard innovation distributions. Thus, including this step in the research will contribute to higher precision in modeling the volatilities. However, the differences are slight.

Table 4 contains the estimated model parameters specified in the formulas 1, 2, and 3 based on the best-fitting innovation distribution. All variables are significant at a 10% significance level, and most parameters are even significant at a 1% level which confirms the relevance of those parameters. The η_1 coefficient has a relatively large magnitude and is significant at a 1% significance level indicating a presence of long-run volatility persistence.

Parameter	S&P500	Hang Seng	Kospi 200	Singapore MSCI 200
μ	0.0635***	0.0626***	0.0217*	0.0186*
	(5.4942)	(3.4935)	(1.302)	(1.3236)
ϕ_1	−0.0764***	−0.0361**	−0.066***	−0.0521***
	(-4.0007)	(-1.9869)	(-3.8021)	(-2.7014)
ω	0.0012***	0.0145***	0.0044***	0.01***
	(3.1016)	(5.7)	(3.9635)	(8.0765)
η_1	0.9993***	0.9911***	0.9966***	0.9882***
	(139788.3)	(12624.7)	(102277.2)	(42689.0742)
η_2	0.025***	0.039***	0.0197***	0.0529***
	(11.4268)	(7.2564)	(3.5648)	(10.7396)
α_1	0.1619***	0.0213***	0.0586***	0.0356***
	(71.784)	1.7983	(4.2505)	(1.9319)
β_1	0.797***	0.8602***	0.8909***	0.8367***
	(265.5238)	(12.3944)	(30.1279)	(11.801)

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 4: Estimated component GARCH parameters. In parentheses the t-statistic is given.

It should be noted, based on table 4, that all η_1 coefficients are close to one, which indicates that the permanent volatility component has a very slow mean reversion. The parameter of the transitory component (α_1) gauges the initial impact of a shock to the component GARCH transitory component and is most profound in the S&P500 future. The parameter β_1 indicates the degree of memory in the transitory component and is significant for all future contracts. Given that the permanent component of volatility parameter η_1 is larger than the sum of the transitory components of volatility ($\alpha_1 + \beta_1$), it can be concluded that mean reversion is slower in the long run. This slow mean reversion in the long run makes the models more stable.

Based on figure 4, the following can be concluded. Firstly, for all future contracts, the permanent component of volatility is more extensive in magnitude and more persistent than the temporary volatility component. For the S&P500 future, this difference seems to be the smallest. For the Asian Tigers, peaks of permanent volatilities are observed around 2012, 2016, and 2020. The peaks of 2016 can be attributed to the Chinese stock market crash of 2015, which started in June and continued into July and August. In January 2016, the Chinese stock market experienced a steep sell-off. For the S&P500 future, this event seemed to have little to no impact on the permanent volatilities. The fact that this event had little to no impact is also visible in the price plots given in figure 1. The peaks in 2020 can be attributed to the global COVID-19 pandemic, disturbing markets worldwide. This event leads to a simultaneous increase of the permanent component of volatilities and the temporary component of volatilities. After a large increase in the temporary component of volatilities, this component even became negative; negative volatility itself does not exist. That the COVID-19 event did have a significant impact on the financial markets is observable in figure 4 and in the price plots given in figure 1.
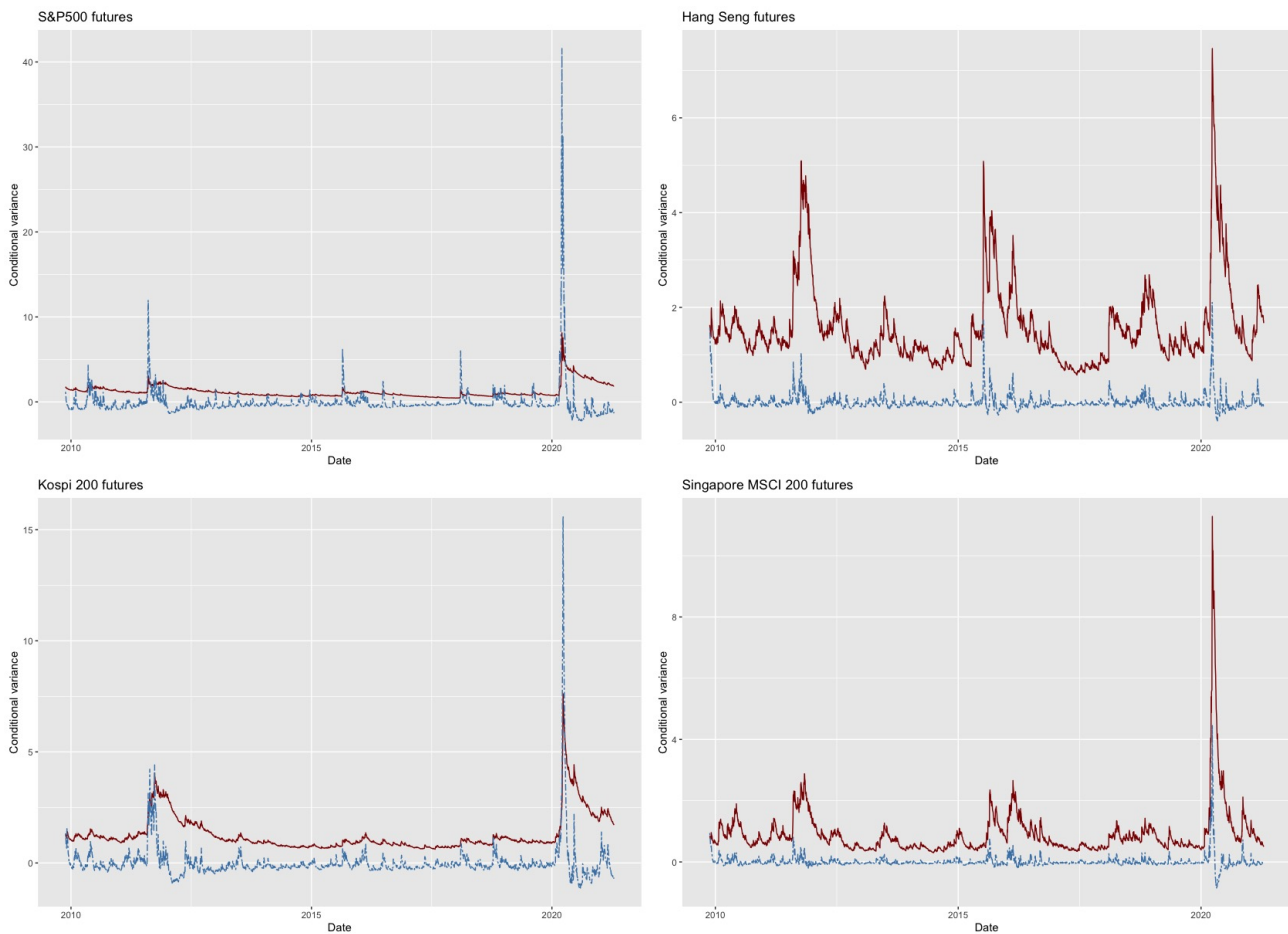

Figure 4: Estimated dynamic permanent volatilities (red line) and transitory volatilities (blue line) for the selected futures.

5.2   Robust quantile regression estimation

After estimating the permanent volatilities components and transitory volatilities components, the best-fitting skewed densities of the futures in the robust quantile regression need to be determined. Finally, robust quantile regression is performed on the median; in table 5 the results are given.

Future contract	Type of volatility	Types of SKD				
		Normal	Student-t	Laplace	Slash	Cont. Normal
Hang Seng	Transitory	933.70	-5029.39	-4678.61	-5014.29	-3776.62
	Permanent	9132.15	4330.17	4450.01	4357.50	5116.49
Kospi 200	Transitory	8822.79	835.19	1735.07	809.00	3658.04
	Permanent	5650.65	251.97	440.40	280.87	1250.34
Singapore MSCI 200	Transitory	875.41	-6271.00	-5615.49	-6287.59	-4172.32
	Permanent	8708.89	2480.91	2929.46	2482.38	3974.28

Table 5: Estimated information measure for the quantile regression under different skewed distributions for $\tau^{0.5}$.

According to the mean of the information criterion obtained from this median regression, given in table 5, the following can be concluded. Firstly, for the Hang Seng futures for both the transitory component of volatility and the permanent component of volatility, the Student t-distribution is the best performing distribution. Secondly, for the Kospi 200 future, for the transitory component of volatility, the Slash distribution is the best performing distribution, and for the permanent component of volatility, the Student t-distribution is the best performing distribution. Thirdly, for the Singapore MSCI 200 future, for the transitory component of volatility, the Slash distribution is the best performing distribution, and for the permanent component of volatility, the Student t-distribution is the best performing distribution.

Underneath, the full-sample results of transitory volatility spill-over effects and permanent volatility spill-over effects from the S&P500 future to the Asian Tigers futures, estimated by robust quantile regression, are given. Based on the best performing skewed distribution, determined in the previous section, robust quantile regression is run at the following quantiles 0.05, 0.20, 0.35, 0.50, 0.65, 0.80, 0.95 for the entire sample. The estimated parameters are given in table 6 and visualized in figure 5.

Future	Type of volatility	Quantilies						
		0.05	0.2	0.35	0.5	0.65	0.8	0.95
Hang Seng								
β_2	Transitory	0.0382***	0.0411***	0.0479***	0.0664***	0.0863***	0.0917***	0.1016***
	Permanent	0.2605***	0.3308***	0.5284***	0.6280***	0.7219***	0.8456***	1.2921***
Kospi 200								
β_2	Transitory	0.3135***	0.2888***	0.3033***	0.3178***	0.3323***	0.4632***	0.4967***
	Permanent	0.3120***	0.4908***	0.6329***	0.7160***	0.7426***	0.7635***	0.8536***
Singapore MSCI 200								
β_2	Transitory	0.0421***	0.0554***	0.0742***	0.0763***	0.0827***	0.0918***	0.1350***
	Permanent	0.1711***	0.2571***	0.3397***	0.4167***	0.5313***	0.6884***	1.0284***

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 6: Estimated transitory and permanent volatility quantile parameters - full-sample

From table 6 it is possible to conclude that all estimated quantile regressions are statistically significant at a 1% significance level, whereas the magnitude of the estimated parameters gradually increases with the level of quantiles used in the regression.

This increase indicates, at least for the full-sample data-set, that volatility transmission from the S&P500 future, as a proxy for the United States financial market, is more intense in periods of increased market turbulence, periods of high volatility. Moreover, for all futures and both types of volatility components, a rising trend is observed. Moreover, all parameters have a positive sign, and therefore the futures can not be used to hedge risk from the S&P500 future. In figure 5, the development of the parameters is plotted.

(a) Hang Seng permanent spill-over effect

(b) Hang Seng transitory spill-over effect

(c) Kospi 200 permanent spill-over effect

(d) Kospi 200 transitory spill-over effect

(e) Singapore MSCI 200 permanent spill-over effect

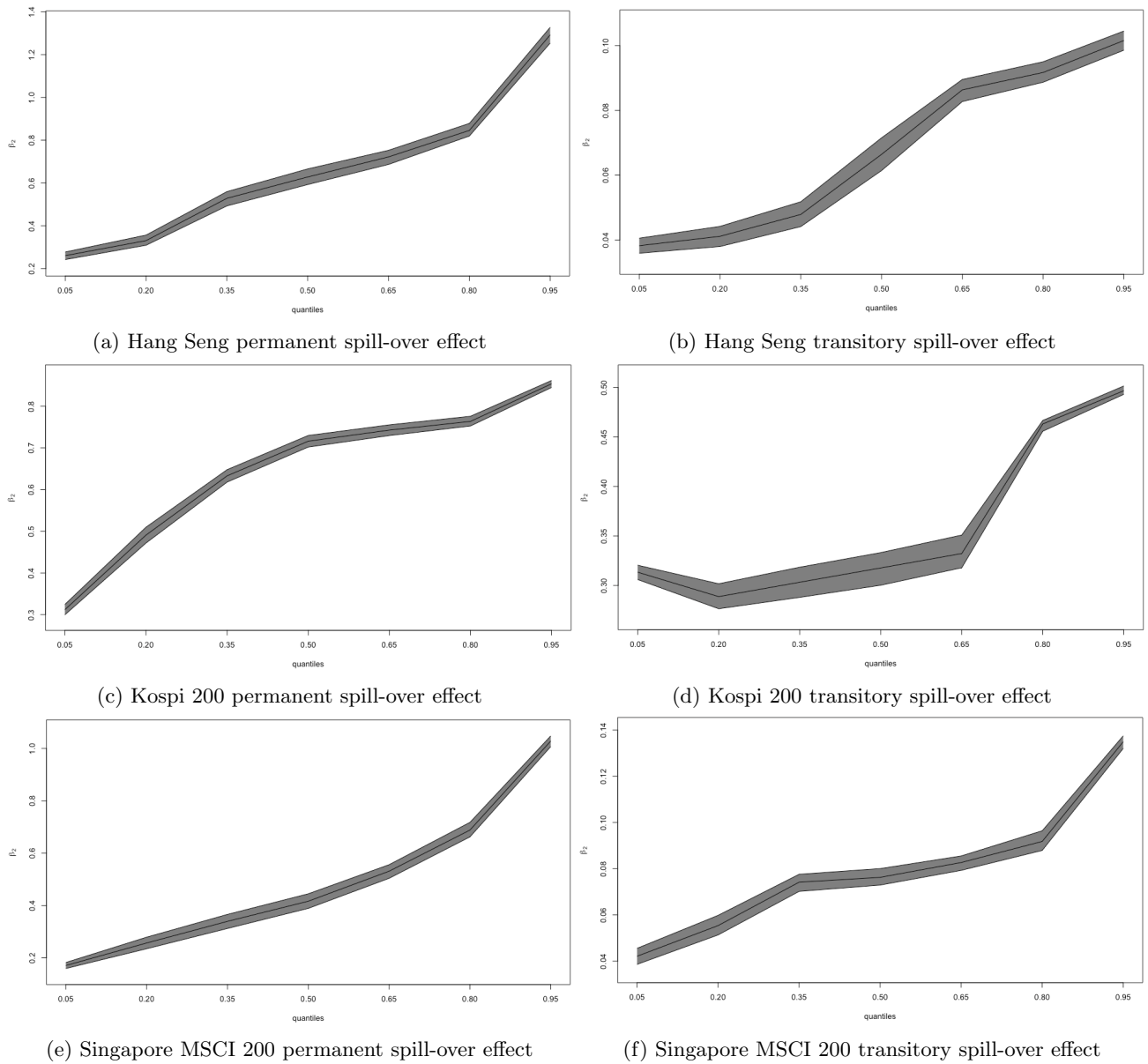(f) Singapore MSCI 200 transitory spill-over effect

Figure 5: Plots for the spill-over effects from the S&P500 future to the Asian Tigers futures.

For the Hang Seng future, as a proxy for the Hong Kong market, and the Singapore MSCI 200 future, as a proxy for the Singapore market, the transitory component of volatility is not highly related to the S&P500 future. However, for the Kospi 200 future, as a proxy, for the South-Korean market, at all quantiles, the transitory component of volatility is almost five times as high as the Hang Seng future and the Singapore MSCI 200 future. Thus, indicating high spillover effects on this component from the S&P500 to the South-Korean market.

For the Singapore MSCI 200 future, the permanent component of volatility is weakly related to the S&P500 future at the lower quantiles. However, at the highest quantiles, the spillover effect from an S&P500 future permanent shock seems to have an amplifying effect on the Singapore MSCI 200 future. Thus, indicating high dependence in the highest quantile. For the Hang Seng future, the permanent component of volatility is moderately related to the S&P500 future. The spillover effect from S&P500 future seems to have an amplifying effect in the highest quantiles for the Hang Seng future permanent volatility. Thus, indicating high dependence in the highest quantiles. For the Kospi 200 future, the permanent component of volatility is highly related to the S&P500 future.

Based on table 6 and figure 5, it becomes possible to conclude the following on the transmission effects between different types of volatility across the quantiles. Firstly, the results indicate that in all

cases, the long-run (permanent) transmission effect is higher than the short-run (transitory) transmission effect, and that particularly applies to the Hang Seng future and the Singapore MSCI 200 future.

According to Ross (1989), information transfer and volatility spillover effects are synonymous; the variance of price changes is directly linked to the rate of information flow to the market. This direct link means that for the volatility transmission, or information transfer, from the S&P500 future, the American market, and the Asian Tigers futures, the Asian markets, short-term information flow has a weaker volatility shock transmission effect than fundamental factors.

6   Robustness check

6.1   Structural breaks detection by modified ICSS algorithm

Given the fact that for this thesis, a relatively long sample is considered, with numerous periods of low and high volatility, in this section, as a robustness check, the difference between short and long-run volatility spillover effects from the United States to the Asian Tigers are investigated for several sub-periods. Živkov et al. (2020) use a modified ICSS algorithm, as explained in subsection 3.3, to detect points of structural changes. For all four futures contracts, the modified ICSS by Sansó et al. (2003) is applied in GAUSS, and in figure 6 the log-returns and the structural breaks are plotted.
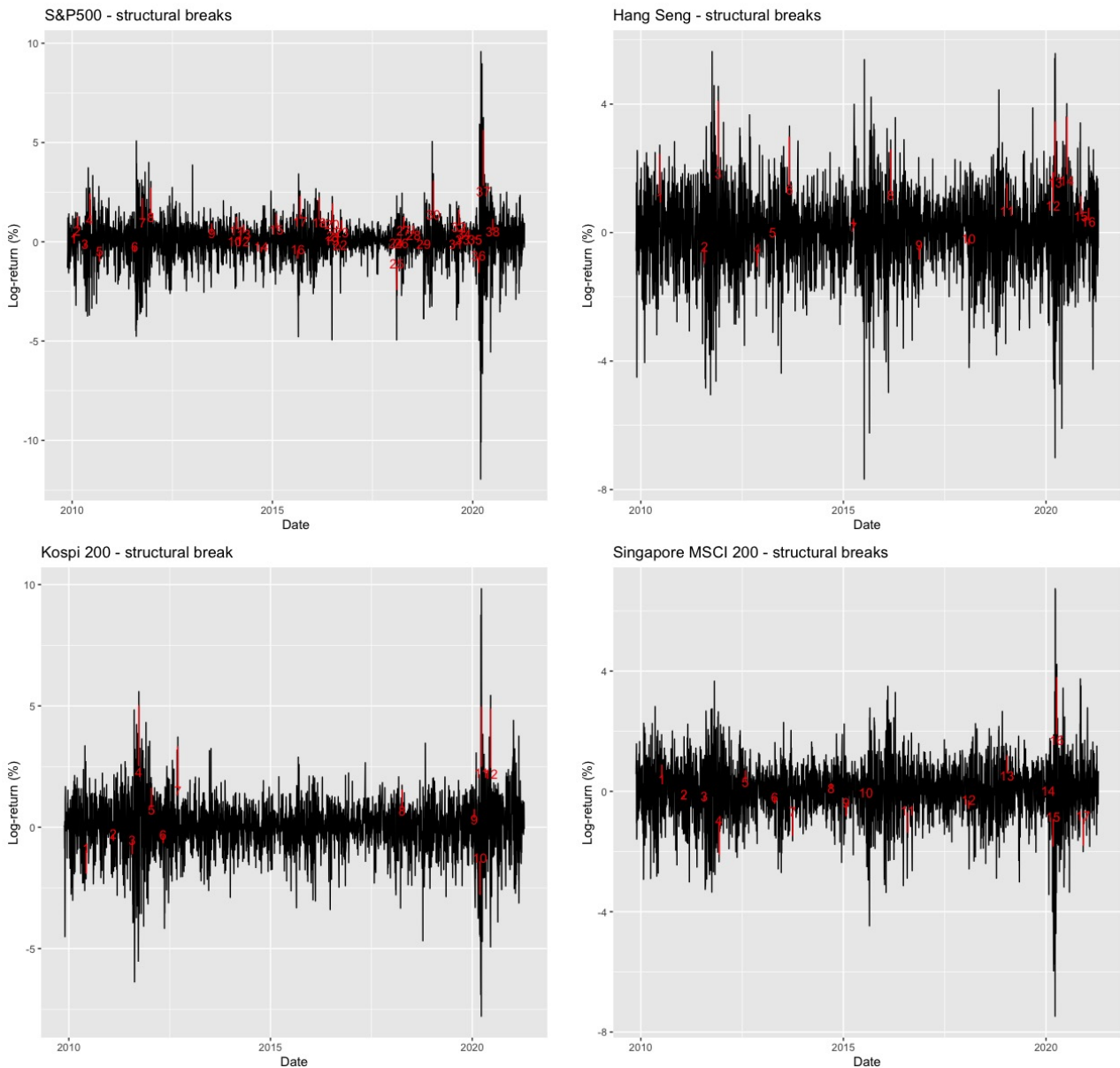

Figure 6: Detected structural breaks via modified ICSS algortihm.

6.2   Sub-sample construction

Figure 6 clearly shows the presence of structural breaks in the log-return data. However, based on figure 6, it becomes possible to conclude that modeling all regimes, all parts between structural breaks, is impracticable. Therefore, it is decided to split up the samples into three groups over time. Namely, the periods: 2009-2014, 2014-2019, and 2019-2021. In table 7, the division of these sub-periods and their standard deviation is given.

Period	S&P500		Hang Seng		Kospi 200		Singapore MSCI 200	
	S.D.	Type	S.D.	Type	S.D.	Type	S.D.	Type
11/20/09 - 12/31/13	1.0557	Moderate	1.0609	Moderate	1.1952	Moderate	0.9382	Moderate
1/1/14 - 12/31/18	0.7844	Calm	0.8234	Calm	0.8099	Calm	0.8442	Calm
1/1/19 - 4/16/21	1.6356	Crisis	1.5649	Crisis	1.5180	Crisis	1.1846	Crisis

Table 7: Breaking points of the sub-samples and standard deviations of the selected index futures contracts.

Table 7 presents the sub-periods bounded with exact dates and accompanying levels of standard deviation in the log-returns for each sub-period. Standard deviations are used to classify the three sub-samples with the lowest, moderate, and highest risk. The highest risk is detected in the third sub-sample relative to the two other sub-samples for all futures. The highest risk in the late sub-sample is expected because the COVID-19 pandemic, which started at the beginning of 2020, shocked international financial markets. For all futures, the early sub-sample, the period after the Global Financial Crisis, also shows relatively high standard deviations; this might be due to the consequences or after-effects of the Global Financial Crisis. The middle period of all futures is relatively calm. These results could be visibly confirmed by analyzing the results in the graphs of figure 6.

6.3 Sub-sample robust quantile regression results

Now that the three sub-samples are classified, the parameters of the robust quantile regression, in the same manner as section 5.1, are estimated. In table 8 the results are given. Overall, the results are highly significant at a 1% confidence level, and all parameters have meaningful magnitude. In order to preserve space, the parameter plots are not given in this thesis but are obtainable by request.

Future	Type of volatility	Quantilies						
		0.05	0.2	0.35	0.5	0.65	0.8	0.95
Hang Seng								
β_2 (Moderate)	Transitory	0.0578***	0.0714***	0.0880***	0.1004***	0.1343***	0.1412***	0.1409***
	Permanent	0.4616***	0.8549***	0.8259***	0.8697***	0.9580***	1.8359***	1.9126***
β_2 (Calm)	Transitory	0.0358***	0.0685***	0.0795***	0.1164***	0.1263***	0.1313***	0.1335***
	Permanent	1.3693***	1.6164***	1.8573***	2.0155***	2.1350***	2.2620***	2.6400***
β_2 (Crisis)	Transitory	0.0242***	0.0281***	0.0283***	0.0292***	0.0406***	0.0407***	0.0863***
	Permanent	0.1775**	0.2319***	0.3098***	0.5467***	0.6680***	0.8763***	0.9141***
Kospi 200								
β_2 (Moderate)	Transitory	0.2952***	0.3427***	0.3688***	0.4087***	0.4510***	0.4889***	0.6530***
	Permanent	0.0713***	0.1566***	0.7764***	0.9571***	1.0469***	1.0910***	1.1479***
β_2 (Calm)	Transitory	0.1292***	0.1649***	0.2078***	0.2303***	0.2859***	0.3528***	0.4673***
	Permanent	0.2094***	0.2967***	0.3632***	0.3696***	0.3831***	0.4156***	0.4578***
β_2 (Crisis)	Transitory	0.3640***	0.4690***	0.4683***	0.4681***	0.4686***	0.5095***	0.5686***
	Permanent	0.6075***	0.6640***	0.7265***	0.7462***	0.7604***	0.7525***	0.7502***
Singapore MSCI 200								
β_2 (Moderate)	Transitory	0.0344***	0.0437***	0.0568***	0.0706***	0.0895***	0.1385***	0.1818***
	Permanent	0.4872***	0.7100***	0.8353***	0.9548***	1.0442***	1.1398***	1.2352***
β_2 (Calm)	Transitory	0.0513***	0.0746***	0.0791***	0.1009***	0.1236***	0.1805***	0.1854***
	Permanent	0.6706***	1.1082***	1.2255***	1.3160***	1.3609***	1.4614***	1.6766***
β_2 (Crisis)	Transitory	0.0492***	0.0753***	0.0756***	0.0763***	0.0765***	0.1229***	0.1564***
	Permanent	0.1572***	0.1925***	0.3218***	0.4314***	0.5271***	0.6556***	0.9857***

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 8: Estimated transitory and permanent volatility quantile parameters - sub-sample

By comparing the full-sample robust quantile regression results in table 6 and the sub-sample robust quantile regression results in table 8 it becomes possible to conclude the following.

6.3.1   Hang Seng sub-sample results

Firstly, for the Hang Seng future, the average parameter values are higher for the first two sub-samples, the calm and moderate periods, than the full-sample average, but the crisis period shows a lower average parameter value. Permanent volatility spillovers seem to have a higher impact on the volatility of the Hang Seng future than transitory spillover effects, although the difference in impact declined over time. One fact to notice is that the spillover effects from the United States to Hong Kong are the strongest in magnitude during the relatively calm periods of standard deviations of the log-returns of both countries; this is interesting because one would expect higher overall spillover effects in times of high volatility swings. The decline of transitory and permanent volatility spillover effects is also an exciting result. However, already indicated in table 6, the magnitude of spillover effects from the United States to Hong Kong is the lowest of all three Asian Tiger economies. Thus, indicating a relatively high level of autonomy. On the contrary, attention still needs to be paid to the fact that the magnitude of spillover effects is an increasing function of the selected quantile, indicating that, although not strongly correlated, there are risk transfers. Nevertheless, in the top quantiles, the permanent volatility spillover seems to have a one-on-one relation, in the calm period, even a almost three-on-one relationship, with the volatility of the Hang Seng future, which could be problematic. Therefore, investing in Hang Seng futures is a non-effective investment decision for decreasing overall portfolio risk by hedging in an investment portfolio with S&P500 futures.

6.3.2   Kospi sub-sample results

Secondly, for the Kospi 200 future, the average parameter values for the transitory spillover effects are higher for the first and last sub-samples, the moderate and crisis periods, than the full-sample average. The calm period shows a lower average parameter value for the transitory spillover effect. Contrary to the Hang Seng sub-sample results, this result indicates a relatively stronger dependency during volatility swings for the Kospi 200. This stronger dependency could be problematic given an economic shock originating in the United States, strongly affecting the South-Korean short-term and long-term volatility levels. Permanent volatility spill-overs seem to have a higher impact on the volatility of the Kospi 200 future than transitory spillover effects, although the difference in impact declined over time. The decline of permanent volatility spillover effects is an exciting result, with the last sub-sample even relatively the lowest effect of all three markets. However, already indicated in table 6, the magnitude of the transitory spillover effect from the United States to South Korea is the highest of all three Asian Tiger economies, indicating a relatively low level of autonomy. This difference in magnitude between South Korea and Hong Kong, and Singapore is shocking. With parameter values which do sometimes have a ten times higher level. Therefore, relatively spoken, the Kospi 200 future is the most disfavourable instrument to diversify risk in a portfolio of S&P500 futures.

6.3.3   Singapore MSCI 200 sub-sample results

Lastly, for the Singapore MSCI 200 future, the average parameter values for the transitory spillover effects are higher for the first two sub-samples, the moderate and calm periods, than the full-sample average. This result is in correspondence with the Hang Seng future but in contradiction with the Kospi 200 future. Overall, there seems to be a decrease in transitory and permanent volatility spillover effects. On average, the permanent volatility spillover effects seem to have decreased from the early sub-sample to the late sub-sample. The permanent volatility spillover effects seem to affect volatility stronger than the transitory volatility spillover effects. The decrease of spillover effects can be interpreted as positive; Singapore became, especially for the permanent volatility spill-overs, less dependent on volatility swings in the United States. However, in the top quantiles, the permanent volatility spillover seems to have a one-on-one relation, and in two sub-samples even a amplifying relation, with the Singapore MSCI 200 future; this could be problematic.

For all Asian Tigers futures, the permanent effect is stronger than the transitory effects in all sub-samples, which means that fundamental information flow causes more significant volatility spillover impact than short-term information flow.

7   Conclusion and discussion of the results

This thesis investigates the transmission of transitory and permanent parts of volatilities from S&P500 futures market to three Asian Tiger futures markets - namely the Hang Seng futures market, the Kospi 200 futures market, and the Singapore MSCI 200 futures market. In the two-step procedure by Živkov et al. (2020). Firstly, transitory and permanent volatilities are estimated based on the optimal component GARCH model. After that, these estimated volatilities are embedded in the robust quantile regression. Moreover, a sub-sample analysis is performed. For structural break detection, the modified Iterative Cumulative Sum of Squares algorithm by Sansó et al. (2003) is used. However, due to numerous structural breaks, the sub-sample is divided on the classification as mentioned earlier. The sub-samples are based on the level of standard deviation. Rightfully modeling financial interrelationships should interest policymakers and investors. This thesis delivered the following results regarding the volatility mechanisms from the United States to the Asian Tigers.

7.1   Full-sample conclusion

All estimated parameters, for both the full-sample findings and the sub-sample findings at all quantiles, of the robust quantile regression are positive, so have a positive sign, magnitude, non-negligible parameter value, and are significant. Based on these results, it is possible to conclude that short-term and long-term volatility shocks originated from the United States futures market spill over to the Asian Tigers futures markets. These results indicate a potential infection risk from shocks originated in the United States futures markets to the futures markets of the Asian Tigers.

For policymakers, this could be a helpful insight for drawing up new financial regulations to decrease the risks associated with the financialization of global economies. For investors in financial instruments like futures contracts, the following is concluded. Given the fact that, that all the Asian Tigers futures markets are net receivers of volatility from the United States futures market, these futures contracts are not suitable as a diversification instrument if the investment portfolio consists merely of S&P500 futures. Based on the conclusion of Živkov et al. (2020), their basic principle says that if volatility from one financial market transmits to another financial market, these financial assets should not be combined in a single investment portfolio.

Looking at the differences between magnitudes of the estimated robust quantile regression parameters at the different quantiles for all the three Asian Tigers futures markets, it is possible to conclude that all estimated parameters do increase at a higher quantile level. In other words, small short-term shocks and small long-term volatility shocks originated from the United States futures markets do have a relatively lower effect on the level of short-term and long-term volatility of the Asian futures markets than larger shocks. This asymmetry indicates an increase in risk transfer if the United States futures market experience a strong volatility swing, a strong shock.

This result is interesting for policymakers because it shows that limiting the probability of high-level shocks in the United States serves the interest of financial risk management in the USA and serves the interest of limiting financial risk of the futures markets of the Asian Tigers. If further or total, global harmonization and financialization of financial markets are set to be (future) goals, financial risk management and planning are no longer a national practice but a global practice.

Again rightfully modeling these financial ties is of high importance. For investors, these results might also be interesting. Knowing the dynamics of volatility shocks, an investor could develop a model that combines the probability of a next large volatility shock, given a present shock, and auto-correlation functions to forecast the magnitude of future volatility levels. Then after the development of this model, the investor could smartly use derivatives products to speculate on volatility shocks, i.e., the investor could implement a straddle investment strategy.

7.2   Sub-sample conclusion

After the full-sample analysis, the intention was to divide the entire data-set into sub-samples through the detection of potential structural breaks by applying the modified Iterative Cumulative Sum of Squares algorithm by Sansó et al. (2003). Like aforementioned, this procedure returned, unfortunately, results which were practically impossible to implement, too many structural breaking points, and therefore the sub-samples are constructed by the level of standard deviation in prespecified date-frames and the classification of calm, moderate, and crisis periods of volatility. Based on the sub-sample analysis, it becomes possible to conclude the following.

The estimated robust quantile regression parameters indicate a (mixed) time-varying nature of the connections, so they are not constant over time. The time-varying nature of volatility transmission effects could be problematic, or at least more challenging, for rightfully modeling financial risk in the global financial system, and this impact the decision-making process of policymakers and investors.

Looking merely at differences in magnitudes over time, for all futures markets, the relationship between the volatility level in the United States futures markets and volatility levels of the Asian Tigers futures markets seems to have decreased. This decrease could be interpreted as something positive; these futures markets became over time less dependent on volatility shocks from the United States and gained more autonomy over their financial stability.

Comparing the early period and the late period, it is possible to conclude the following. Firstly, for all Asian Tigers futures markets, the permanent spillover effect decreased over time, so fundamental information flow from the United States futures markets became less critical for permanent volatility levels in the Asian Tigers futures markets.

However, for some sample periods, the estimated parameter value is still one or larger than one, implying an amplifying spillover effect from fundamental information flow. This amplifying effect is potentially problematic as the permanent part of the volatility of the United States heavily affects not only their financial system but also the financial systems of the Asian Tigers.

Like aforementioned, to establish a stable global financial system, policymakers should try to limit national risk levels and serve the common good by financial regulations that take into account the inter-dependencies in the global financial system.

The transitory spillover effects, so instant information flow, from the United States to the Asian Tigers also decreased from the beginning of the sample period to the end of the sample period. This decrease could, like the decrease of permanent spillover effects, be interpreted as positive. The Asian Tigers also, in the short-run, gained more autonomy over the stability of their financial futures markets. However, especially for the Hang Seng futures markets, volatility still spills over from the United States, and again policymakers and investors should keep this in mind in their decision-making process.

The following is concluded based on the futures markets separately.

For the Hang Seng future, the transitory spillover effects are relatively the lowest, and the early and middle sub-sample exhibited a relatively high level of permanent spillover effects originated from the United States. Interestingly, both the spillover effects were the lowest during the period, with the highest standard deviation for both the Hang Seng futures market and the United States futures market. One would expect a priori the opposite, so more potent spillover effects during turbulent times.

For the Kospi 200 futures market, it can be concluded that relatively the market is most strongly intertwined with the United States futures market, especially regarding the transitory spillover effects. For the Kospi 200 futures market, it is also proven that the volatility spillover effects are more negligible in magnitude during turbulent times. This fact should be taken into consideration.

For the Singapore MSCI 200 futures market, the magnitude of volatility spillover effects decreased during the crisis period. In other words, according to the late sample estimated short-term volatility spillover effects and long-term volatility spillover effects, the following can be concluded. The Kospi 200 futures market is most risky on both the short-term and long-term effects. The Singapore MSCI futures market is riskier given the short-term effects relative to the Hang Seng futures market. The Hang Seng futures market is riskier given the long-term effects relative to the Singapore MSCI futures market.

So to sum this up, by splitting the conditional volatilities into the permanent volatility part and the transitory volatility part, it can be assessed which of the two factors- fundamental long-run factors vs. market sentiments (short-term investor behavior), that originated from the United States futures markets, have a more profound effect on the volatility of the Asian Tigers futures markets. According to the results, it can be concluded that the permanent effect has a more substantial effect relative to the transitory effect, which means that fundamental news flow has a more significant influential effect than short-term information flow.

These results could help market participants, such as investors, policymakers, and regulators, understand what lies behind the transmission effect between the United States futures market and the Asian Tigers futures markets and how they should behave during different market conditions.

7.3   Research limitations and suggestions for further research

Although the research results are satisfying; there is still room for improvement in the research design.

Firstly, the chosen data source www.investing.com is an open-source and free data provider; more reliable price data could be obtained by using the data of professional parties like Bloomberg. Unfortunately, this data source was not accessible.

Secondly, the modeling of an abstract phenomenon like volatility is based on assumptions. Namely, that log differences in opening or close price are a good proxy for the volatility of a financial asset. This assumption might, in fact, not be the case; this method does not utilize intra-day data. Applying intra-day data could better model the transitory spill-over effects, immediate news flow, and the results might be more meaningful. Unfortunately, this data was not available, but studying intra-day data could be interesting for further research. One challenge to keep in mind is the matching of data sets over time given different time zones.

Thirdly, the chosen research methodology, applying a component GARCH model with regimes, is only one method to investigated volatility, and the results should be tested and hopefully confirmed by applying different volatility modeling methods. Nevertheless, the current research methodology could also be extended by applying different GARCH volatility and different innovation distributions.

Fourthly, the component GARCH model is based on past data, and although in-sample auto-correlation is observed in the lagged time-series values, this does not guarantee that the future will repeat these patterns. On the other hand, for the in-sample fit, still significant autocorrelation was present in further lags. Therefore, one possible way to contain more information into the component GARCH model is to apply volatility models with a higher-order updating equation structure. Further research can study if applying a higher-order structure significantly outperforms the single-order component GARCH model structure.

However, which is in disregard with the results from the auto-correlation functions, the fact that the parameters of interest varied over time became apparent during the sub-sample analysis. One way to partly capture changing volatility dynamics, besides establishing different regime types, is to build a model with a moving estimation window and re-estimate the parameters of interest every day. Inoue, Rossi, Jin, and Chen (2013) explain how to implement a rolling estimation window. With

sub-samples specified as regimes, the fixed estimation method was preferred over a moving window estimation method because it saved computing power. However, especially for professionals, the moving window estimation method should be implementable due to modern-day computers and their increased computing power. One disadvantage of the moving window estimation method is that it still possibly adjust slowly to changing volatility dynamics. Therefore, the estimation window size preferably needs to be adjusted. Nevertheless, this research design could be interesting for further research.

Lastly, the frequentist method is applied; it would be interesting to use an alternative approach. One alternative approach is the Bayesian estimation approach, which does allow for prior beliefs. A Bayesian statistician utilizes parameter uncertainty more naturally than classical statisticians into account in decisions and forecasts based on forecasts. Thereby, the Bayesian statistician is speaking in terms of the probability distributions of parameters rather than merely focusing on rejecting a hypothesis. It would be interesting to study if this alternative estimation method improves the transitory and permanent parts of volatility. The theory of Bayesian statistics for financial risk management is given by Ardia (2008). An example paper of this alternative approach for financial risk management is Ardia and Hoogerheide (2014).

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