Directed Studies: ECON 685

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Contents

1 Introduction

In the dynamic landscape of global financial markets, the interdependence between emerging and developed economies has become increasingly pronounced, particularly in the realm of volatility transmission. Volatility spillovers, defined as the transmission of volatility shocks from one market to another, have emerged as a critical area of study in understanding the interconnectedness and risk dynamics across diverse economic spheres. This paper delves into the intricate phenomenon of volatility spillovers from emerging economies to developed economies.

The past few decades have witnessed a significant shift in the global economic paradigm, with emerging economies assuming a more prominent role in the international financial system. Rapid economic growth, financial market liberalization, and increased integration into the global economy have positioned emerging markets as key players in driving both regional and global economic dynamics. Consequently, any fluctuations or shocks in these economies reverberate across borders, impacting not only their regional counterparts but also exerting discernible effects on developed economies.

One of the primary motivations behind studying volatility spillovers is the recognition of their potential to destabilize financial markets and amplify systemic risk. As emerging markets become increasingly interconnected with developed economies through trade, investment, and financial linkages, the transmission channels for volatility shocks have expanded, rendering the global financial system more susceptible to contagion effects. Understanding the patterns and dynamics of volatility spillovers is, therefore, imperative for policymakers, investors, and market participants to effectively manage risk and safeguard financial stability.

Moreover, volatility spillovers have significant implications for portfolio diversification, asset pricing, and risk management strategies. Investors seeking to construct well-diversified portfolios must account for the interconnectedness between emerging and developed markets to mitigate potential downside risks and optimize returns. Furthermore, policymakers must adopt proactive measures to enhance market resilience and contain the propagation of volatility shocks, particularly during periods of heightened uncertainty or financial stress.

Against this backdrop, this paper employs a comprehensive empirical framework to analyze the spillover dynamics of volatility from emerging economies to developed economies. By examining the transmission channels, magnitudes, and persistence of volatility spillovers, this study aims to contribute to the existing literature on international finance and provide valuable insights for both academic research and practical applications in risk management and investment decision-making.

2 Data and Methodology

This study investigates the volatility spillover effects between the United States and four emerging markets: Mexico, Saudi Arabia, Korea, and Taiwan. These markets were selected based on their significant trade relationships with the United States, reflecting diverse economic structures and trade orientations. Daily closing prices data spanning from 2010 to 2024 were meticulously collected for each market, providing a comprehensive dataset for analyzing long-term trends and dynamics in financial markets.

Logarithmic returns were calculated from the daily closing prices of each market, following established methodologies in financial analysis. Subsequently, a series of statistical tests were conducted to assess the normality, correlation, and independence of the returns. These tests are essential for validating the underlying assumptions and relationships in the data, ensuring the robustness of subsequent analyses.

The log returns of each market were fitted into Symmetric Generalized Autoregressive Conditional Heteroskedasticity (SGARCH) models, a widely used framework for modeling the conditional volatility of financial time series data. Model selection criteria, including the Akaike Information Criterion (AIC), log-likelihoods, and autocorrelation function (ACF) of residual analysis, were employed to determine the optimal order of the SGARCH model. This rigorous process ensures the selection of a model that effectively captures the volatility dynamics of the data.

Conditional volatilities were then extracted from the fitted SGARCH models, representing the time-varying standard deviations of the log returns. These volatilities offer insights into the changing levels of risk across the markets over the study period. Granger causality tests were subsequently conducted to explore the presence and directionality of volatility spillovers between the United States and the selected emerging markets. This analysis contributes to a deeper understanding of the transmission mechanisms of financial shocks among the studied economies, providing valuable insights into global financial market dynamics.

3 Review of Literature

The globalization of financial markets has led to increased interconnectedness between emerging and developed economies, resulting in heightened attention to volatility spillovers. Emerging markets, characterized by rapid economic growth, dynamic financial systems, and evolving market structures, have emerged as significant contributors to global financial market dynamics. Understanding the transmission of volatility from emerging to developed markets is critical for policymakers, investors, and market participants to effectively manage risks and enhance financial stability.

Early studies predominantly focused on the transmission of volatility from developed to emerging markets, driven by factors such as global economic shocks, financial crises, and changes in monetary policy (Forbes & Rigobon, 2002). However, recent research has increasingly examined the reverse direction of spillovers, highlighting the growing influence of emerging markets on global financial markets (Bekaert & Harvey, 2000).

A key theme in the literature is the identification of transmission mechanisms through which volatility spillovers occur. These mechanisms include trade linkages, financial contagion, capital flows, investor sentiment, and policy responses (Dungey et al., 2017). For instance, trade linkages between emerging and developed economies can transmit shocks through changes in export demand, supply chain disruptions, and commodity price movements (Kose et al., 2008). Financial contagion, on the other hand, occurs when negative shocks in one market spill over to others through interconnected financial institutions and markets (Claessens et al., 2012).

Empirical studies employ various econometric techniques to analyze volatility spillovers, including co-integration analysis, Granger causality tests, vector autoregressive models, and multivariate GARCH models. These analyses provide insights into the magnitude, direction, and persistence of volatility spillovers between emerging and developed markets (Diebold & Yilmaz, 2012). Additionally, researchers explore the role of macroeconomic factors, such as exchange rate movements, interest rate differentials, inflation, and geopolitical events, in driving volatility spillovers (Huang & You, 2015).

The literature also discusses the implications of volatility spillovers for policymakers, investors, and market participants. Policymakers need to design robust macroeconomic and financial policies to mitigate the impact of external shocks and maintain financial stability (Fratzscher, 2012). For investors, understanding volatility spillovers is crucial for risk management and portfolio diversification strategies (Fernández et al., 2016). Insights from the literature inform asset allocation decisions and help investors navigate the complexities of global financial markets.

In conclusion, the literature on volatility spillovers from emerging markets to developed markets highlights the complex interdependencies and transmission mechanisms inherent in global financial markets.

4 Stylized Facts

The below is a summary of findings from the previous sections.

Table 1: Summary Statistics of Returns

Country	Count	Mean	Median	SD	Skewness	Kurtosis
Taiwan	2218	0.0002479	0.0007743	0.0097521	-0.5450061	3.956823
Mexico	2218	0.0001381	0.0002618	0.0101467	-0.5009711	3.589466
Korea	2218	0.0001488	0.0003937	0.0103972	-0.2997591	6.974048
Saudi	2218	0.0004128	0.0002317	0.0111743	-0.6819229	20.498449
Hong Kong	2218	-0.0003231	0.0000753	0.0126915	-0.1041092	3.323820
China	2218	-0.0002059	0.0000259	0.0127727	-0.8184966	6.648861
USA	2218	0.0002949	0.0005009	0.0109830	-0.5888374	10.354403
Canada	2218	0.0000757	0.0006891	0.0094531	-1.6565900	37.310599
UAE	2218	-0.0000880	0.0000000	0.0239387	0.6255473	6.078954

In order to determine the model type and fit, diagnostic tests have been run on the returns of each index. The chapter is a breakdown of the analysis on the independence, stationarity, serial correlation and normality of the series returns.

4.1 Taiwan

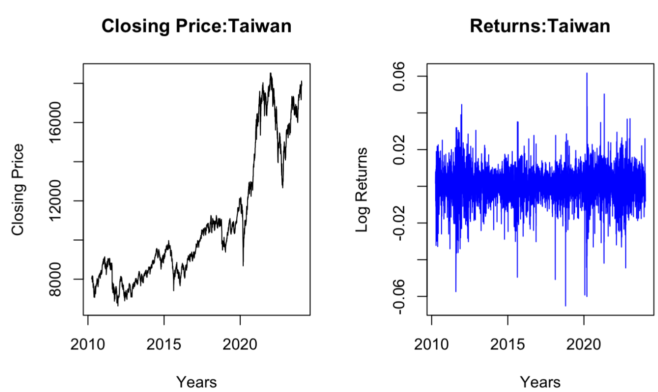
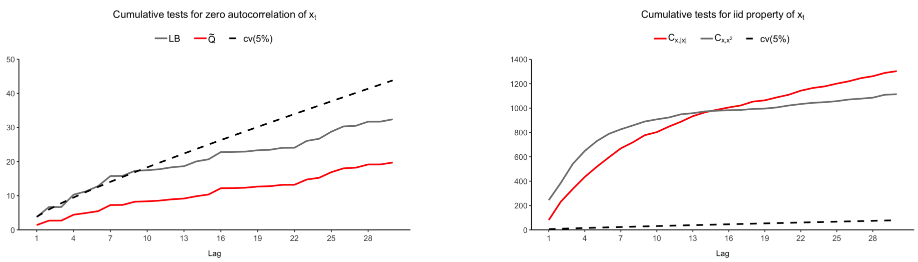


Figure 1: Returns and Closing Price from 2010 to 2024

The returns and closing prices of the Taiwan Stock exchnage has been analyzed from 2010 up to 2023. The closing prices follows an overall upward trend with some periods of volatility post 2020 (COVID 19). The variations in stock prices are also captured in the returns. The daily returns exhibit considerable volatility. The fluctuations appear to the greatest around the pandemic.

The DGP test statistic is used to test for the presence of serial correlation in the Taiwanese stock returns. The DGP test is captured by the red line. Since the test statistic lies below the five percent level, the null hypothesis cannot be rejected. There is no serial correlation in the returns.
On understanding the features of the returns from Taiwan , the iid test reveals that the data in not iid, this could be because of correlation or non-stationarity.



Autocorrelation IID

Figure 2: Testing of autocorrelation and iid in Taiwan Returns

It is also imperative to determine the distribution of the returns series. A qq plot is used for this purpose. Similar to majority of empirical studies on returns, the Taiwanese returns too does not follow a normal distribution. It is characterized by fat tails. The KPSS test was employed to ascertain whether or not the returns were stationary. The KPSS test statistic was found to have a p-value of 0.09558. indicating that the data was stationary.

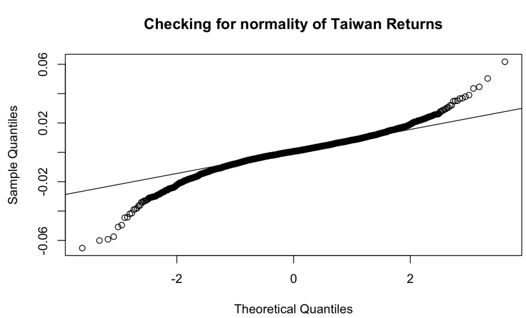


Figure 3: Distribution of Taiwan Returns

Given that there is no dependence, it would be appropriate to fit a GARCH model. The GARCH order selection is carried out using the fGarch package on

R and a vanilla GARCH model is fitted to extract the conditional volatilities in the returns. The order with the least largest log likelihood and smallest AIC was selected.

4.2 Korea

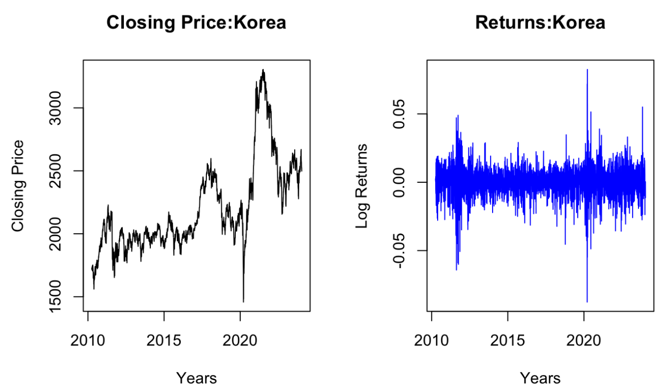
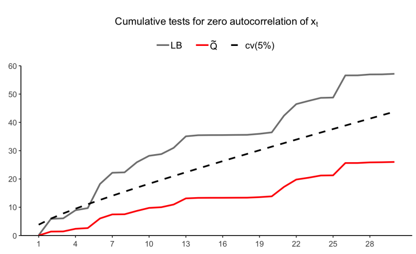
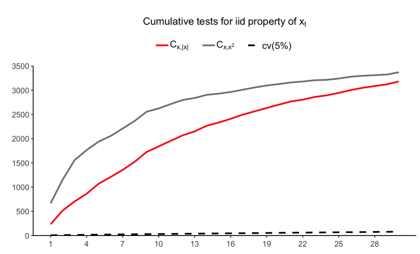


Figure 4: Returns and Closing Price of KOSPI from 2010 to 2024

The closing price of the Korean Composite Index follows an upward trajectory with three significant peak, post 2010, around 2016 and 2017. This is followed by a steep decline in prices around COVID after 2020. The volatility in returns reflect the volatility spike around 2020-2021. There is also some noticeable variations post 2010 in the returns.



Autocorrelation



IID

Figure 5: Testing of autocorrelation and iid in Korean Returns

Given the significant volatility present in the returns series an analysis on the correlation structure of the lags, independence and distribution will aid in determining the model fit. The DGP test statistic falls below the grey dashed line for up to thirty lags. The test, fails to reject the null as it falls within the five percent level. The KOSPI[Korean Composite Index] Returns are therefore not correlated. The returns however are not iid since the the returns are correlated with the squares and the absolutes.

A significant portion daily log returns on the KOSPI fall on the qqline. Deviations from the line are observed around the tails. The fat tails on the distribution could suggest that the returns are not Gaussian. On testing for

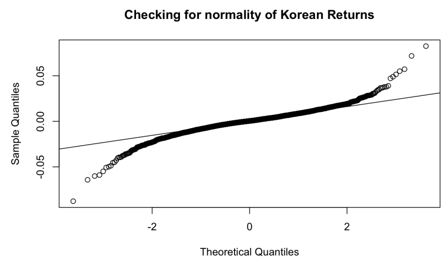


Figure 6: Distribution of Korea Returns

Stationarity using the KPSS test, the resultant p value of 0.06437 falls below the critical value of 0.032 at the five level. The returns are stationary. Similar to the Taiwanese returns, the Korean returns are uncorrelated, stationary, non-normal and non-iid.

4.3 Mexico

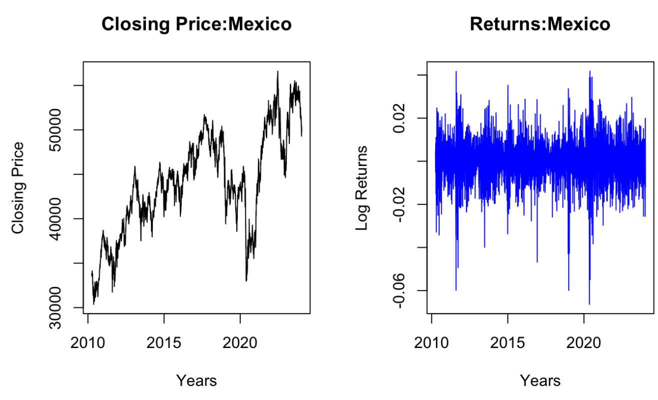
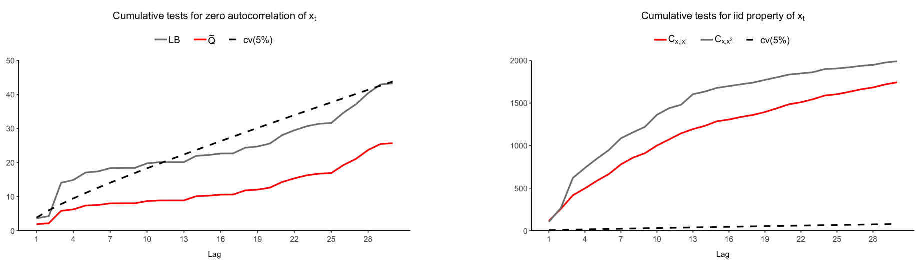


Figure 7: Returns and Closing Price of BMV from 2010 to 2024

The Closing prices of the Mexican BMV index presents significant volatility with sharp spikes and troughs. The steepest decline in the prices occurs around the pandemic.Large volatility spikes are observed during the early 2010s. This could be due to the economic slowdown post the 2008 crisis or the spillovers from the euro-debt crisis. An absence of correlation is observed when considering the DGP test statistic at the five percent level over the thirty lags. The returns on the BMV Mexico index is found to be neither independent nor identical across the squares and absolutes. The non-iid nature could be attributed towards non-stationarity or correlation.



Autocorrelation IID

Figure 8: Testing of autocorrelation and iid in Mexico Returns

The qq plot of the Mexican BMV daily log returns aid in determining the normality in the distribution. The fat tailed distribution goes on to confirm the empirical evidence of fat tails in financial data. The Mexican daily log returns are therefore not gaussian. With a p value of 0.0422, the daily log returns were

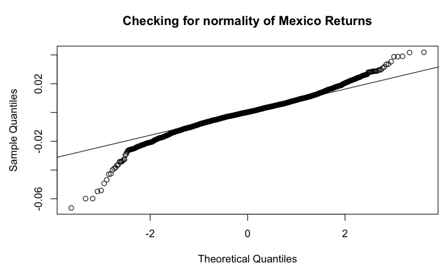


Figure 9: Distribution of Mexico Returns

found to be stationary over the 13 year period. Given the lack of dependence, an SGarch model may be appropriate.

4.4 Saudi Arabia

The differenced log returns Tadawul Exchange is used to fit the GARCH model and extract the volatilises. Diagonstic tests on the estimated returns will guide the model selection. A preliminary analysis of the closing prices and returns.The 2013 to 2014 peak was driven by the non-oil sectors. The higher peak post 2020, it could be due to ARMACO reporting a 121 billion profit for 2022.

The daily returns indicate at peaks followed by troughs and smaller variations owing to market adjustment. The volatility appears to decay slower around 2015 when compared to 2020.

The test of serial correlation and iid are done on the daily log returns of the

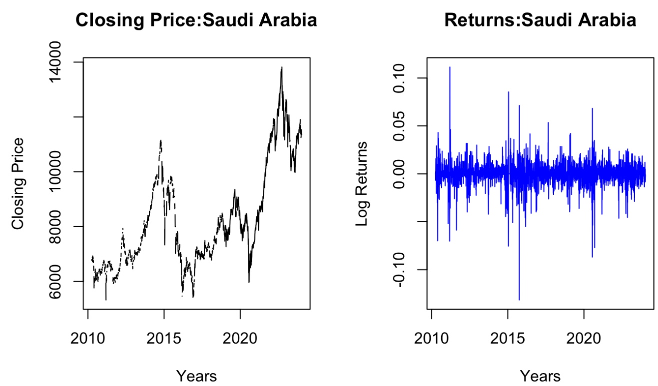
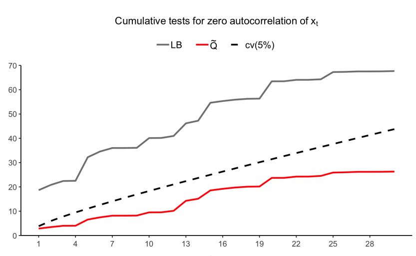
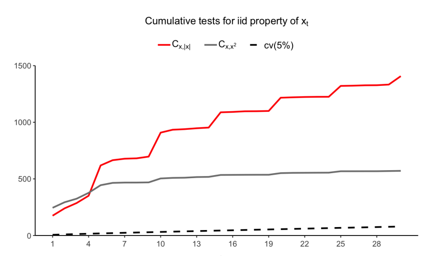


Figure 10: Returns and Closing Price of Tadawul from 2010 to 2024

Tadawul Stock Exchange. The null hypothesis of no autocorrelation is accepted and the alternate of autocorrelation is rejected. The Q statistic line falls within the five percent level. The returns are also found to be non-iid. The returns are found to be correlated with the square and absolute returns at the five percent level.



Autocorrelation



IID

Figure 11: Testing of autocorrelation and iid in Tadawul Returns

The theoretical and empirical quantiles of the daily returns on the Tadawul Exchange is fitted on the quantile-quantile plot. A significant portion of the returns fall on the qq line. The returns appear to deviate from the qq line around the tails. The large deviations indicate that the returns could have a fat tail and is not normal.

The KPSS statistic of 0.0636 suggests that the returns series is stationary. Since the estimated P value falls below the critical value at five percent, the statistical properties of the tim series does not change over time. There is no need to difference the data.

Given that the returns series is stationary, non-correlated, non-iid and non-normal, a GARCH model will help estimate the volatilities in the index returns over the thirteen year period.

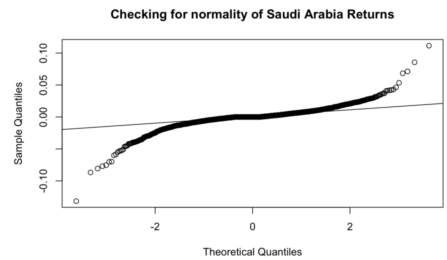


Figure 12: Distribution of Saudi Arabian Returns

4.5 USA

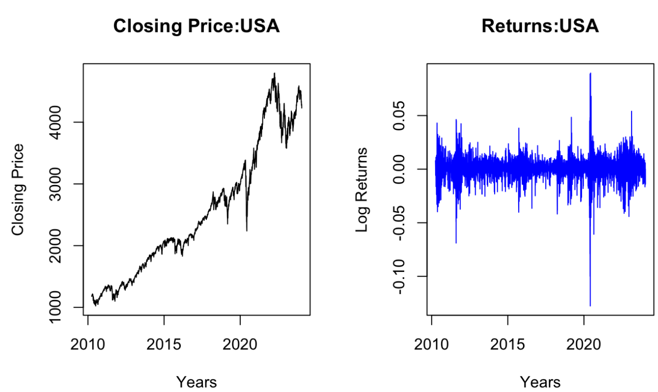
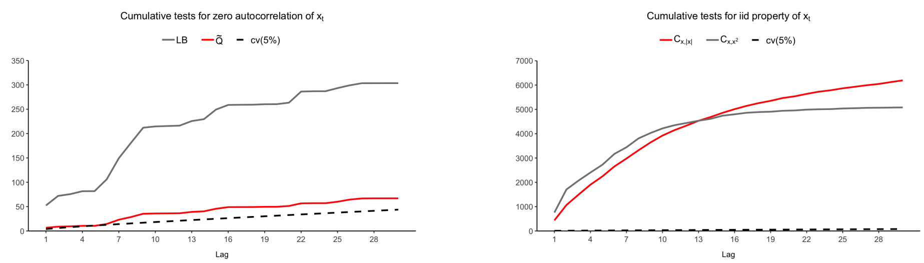


Figure 13: Returns and Closing Price of S&P 500 from 2010 to 2024

The closing prices of the S&P 500 follows an upward trend from 2010 to 2023 with small dips followed by rebounds. The upward trend could be due factors such as tech optimisim and monetary policies. The prices start at as low as \$1000 and cross over \$4000 post COVID. This could be due to the stimulus and increased vaccine uptake. The daily log returns reflect the bullish trend characterized by significant spikes and drops.



Autocorrelation IID

Figure 14: Testing of autocorrelation and iid in S&P 500 Returns

Unlike the returns from the selected emerging markets, the returns of S&P 500 fails to reject the null hypothesis. The DGP statistic, represented by the red line lies above the critical values at the five percent level. The log returns of the US index is therefore serially correlated upto 30 lags.

The returns were also tested for iid properties. The results indicate that the returns are correlated with absolute and squares. This is seen the plot where in the red and grey lines lie over the dashed line.

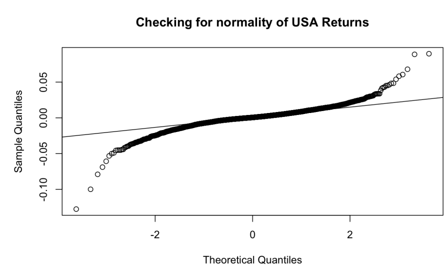


Figure 15: Distribution of S&p 500 Returns

The qq plots is used to assess the probablity distribution of the returns. The plot of the empirical quantiles against the theoretical quantiles suggest the daily log returns do not follow a gaussian distribution. The deviation from normality is captured by the tails of the distribution.

The series was also found to have a pvalue of 0.0266. Given that the test statistic falls below the critical value of 0.423, the KPSS test fails to reject the null hypothesis of stationarity.

4.6 China

There is a downward trend in prices upto 2015. This could be due China's economic slowdown as well regulatory corrections. There is some observable volatility in the returns and closing prices around 2015- 2016. This because the stock market bubble burst and the A-shares value fell by one-third. The closing prices peaked in 2014. Shanghai Composite Index grew by 150%. The Chinese investors lost about EUR 5 trillion that summer. The risk of contagion was pronounced.

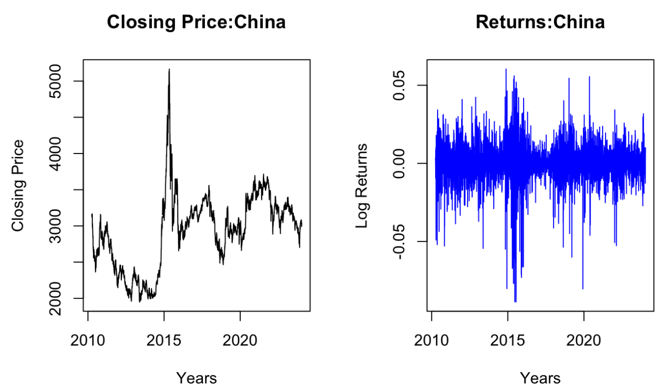
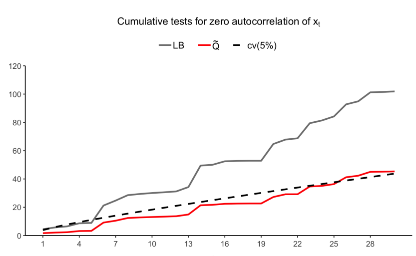
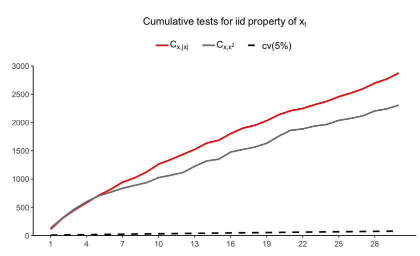


Figure 16: Returns and Closing Price of SSE from 2010 to 2024



Autocorrelation



IID

Figure 17: Testing of autocorrelation and iid in S&P 500 Returns

The correlation structure within the lags appears to be unclear over the thirty lags. The data however is not iid or normal. At 0.0653 the KPSS test rejects the alternate of unit root and accpets the null of stationairty.

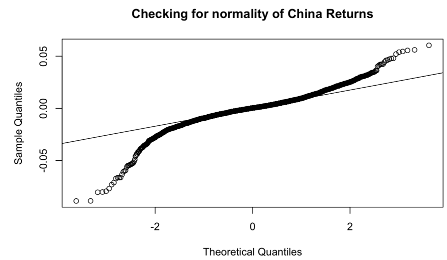


Figure 18: Distribution of S&p 500 Returns

4.7 Canada

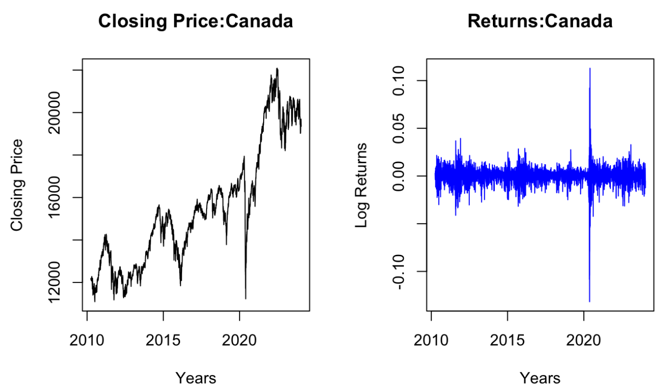
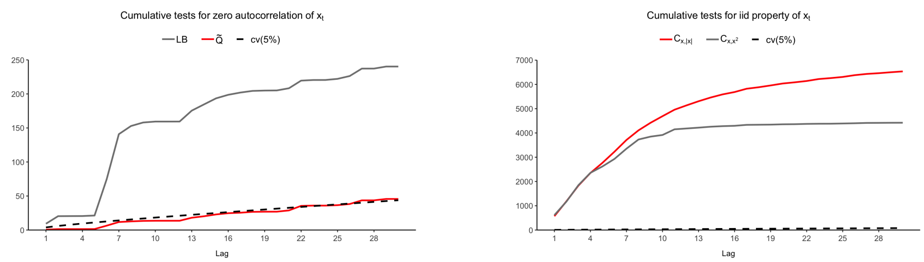


Figure 19: Returns and Closing Price of Toronto Stock Index from 2010 to 2024

There exists a general upward trajectory in the closing prices of the Toronoto Stock Exchange. There appears to be three peaks and one makor drop in prices. The is a spike in closing prices in 2010 followed by another in 2015 and finally after 2020. The variations in returns seem. Periods of heightened volatility, indicated by larger fluctuations in daily log returns, may coincide with significant market events such as economic downturns, geopolitical tensions, or policy changes.

The results from the ac test are inconclusive as the DGP statistic marginally deviates above the five percent critical value. Given that the LB test is over the dashed line, the null hypothesis of no correlation is rejected and the alternate is accepted. The returns were also found to be non-iid.

Similar to the returns distribution observed so far, the TMX returns follow a non-normal distribution as well represented by the fat tail deviations from the



Autocorrelation IID

Figure 20: Testing of autocorrelation and iid in TSX 500 Returns

line of equality. The pvalue of 0.01987 from the KPSS test fails to reject the null hypothesis at the five percent level. The returns therefore are not gaussian. The deviation from iid could be due to the presence of correlation in the data.

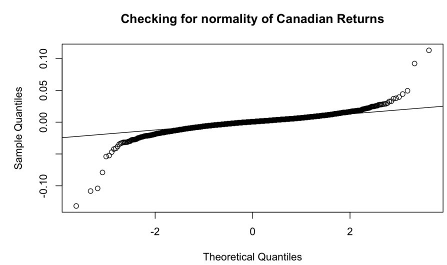


Figure 21: Distribution of S&p 500 Returns

4.8 Hong Kong

The left graph depicts the closing price, which exhibits significant volatility with sharp peaks and troughs throughout the years. The trend appears to be overall upward, with the closing price reaching its highest levels around 2020.

The right graph shows the log returns, which represent the daily percentage changes in the stock market index. The returns exhibit a high degree of fluctuation, with numerous spikes indicating large positive and negative daily movements. The volatility appears relatively consistent across the time period, with no clear patterns of increasing or decreasing volatility.The closing price graph captures the long-term trend, while the returns graph illustrates the day-to-day fluctuations and risk associated with investing in this market

The autocorrelation structure of the HKEX returns suggest that the data is not serially correlated. This is because the DGP test does not reject null at

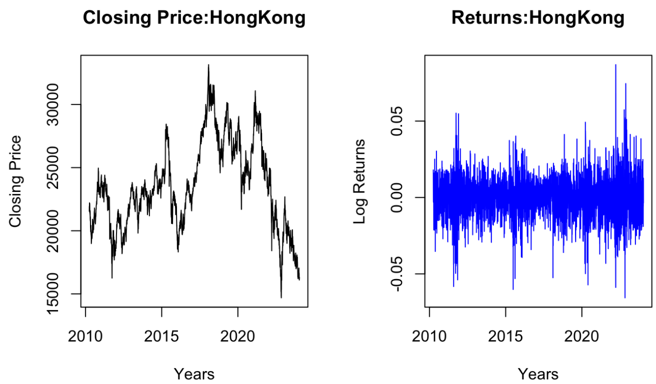
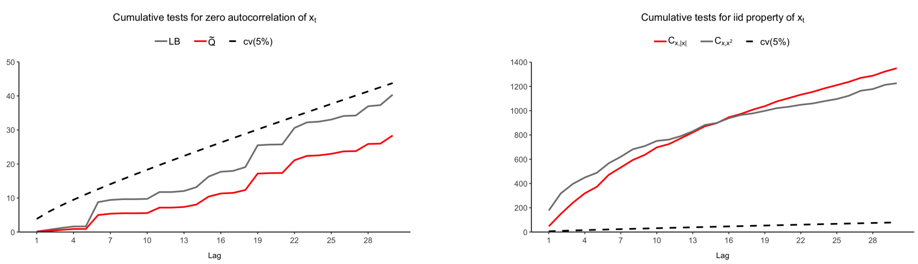


Figure 22: Returns and Closing Price of Hong Kong Index from 2010 to 2024



Autocorrelation IID

Figure 23: Testing of autocorrelation and iid in Hong Kong Returns

the five percent level. Unlike the autocorrelation results, the red line lines well above the five percent level. The returns are found to be non-iid and the null hypothesis is rejected.

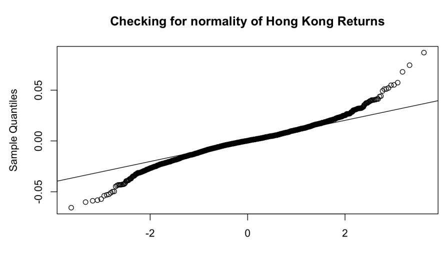


Figure 24: Distribution of HKEX 500 Returns

The distributions on the qq plot show that the HKEX daily log returns are not normal.tHE kpss test rejects the alternate of unit root since the pvalue 0.0697 is less than the critical value.

4.9 UAE

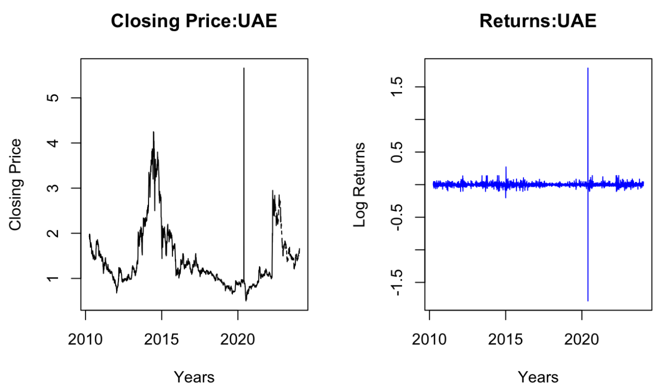
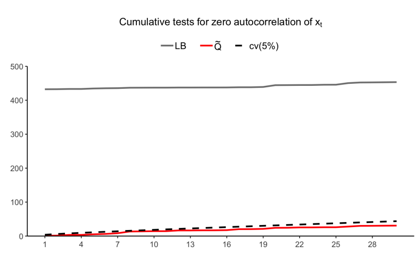
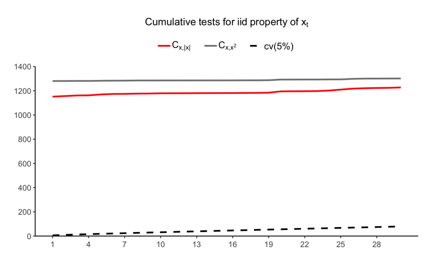


Figure 25: Returns and Closing Price of Dubai Financial Market from 2010 to 2024

There appears to be a period of recovery in the closing prices of DFM after 2008. The Dubai Exchange appears to peak around 2015 and is followed by a very sharp spike in 2020. The retruns suggest that variationsare relatively minimaly with one pronounced fluctation around 2020.
This occurs because serially correlated returns tend to cluster together, leading



Autocorrelation



IID

Figure 26: Testing of autocorrelation and iid in DFM Returns

to periods of high volatility followed by periods of low volatility, which may not be adequately captured by traditional volatility estimation methods. In case of the returns from the Dubai Financial Market, the data clearly fails to rejects the null hypothesis of no correlation. The data is also found to be non-iid. This could be because of the autocorrelation, heteroscedasticity or volatility clustering.

The x-axis represents the theoretical quantiles (values) of a normal distribution, while the y-axis shows the sample quantiles of the data being analyzed (UAE Returns). If the data follows a normal distribution, the points should approximately lie on a straight diagonal line. However, the points deviate from the diagonal line, particularly in the upper and lower tails, indicating that the UAE Returns data likely does not follow a normal distribution. The data was also found to stationary.

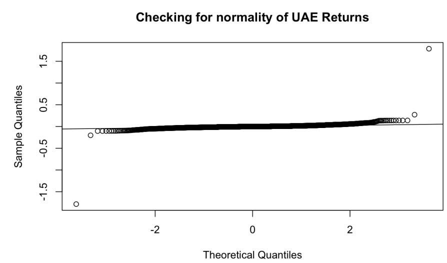


Figure 27: Distribution of DFM Returns

5 GARCH Analysis

5.1 Choice of Model

Country	iid	autocorrelated	normal	Stationary
Saudi Arabia	No	No	No	Yes
Taiwan	No	No	No	Yes
Rep. of Korea	No	No	No	Yes
Mexico	No	No	No	Yes
USA	No	Yes	No	Yes
China	No	Yes	No	Yes
Hong Kong	No	No	No	Yes
UAE	No	No	No	Yes
Canada	No	Yes	No	Yes

The table above is a summary of the stylized facts. It is clear that most of the economies analyzed followed a non-normal distribution and were non-iid. Further, the returns were found to be stationary. These features make it appropriate for fitting GARCH models. An ARMA-GARCH is fitted for China, Canada and USA since the returns exhibit dependence. The Emerging Markets however did not show signs of serial correlation. Therefore,an SGARCH is fited to the returns series. The order selection is done by choosing the model with the smallest Akaike Information Criteria. The AIC is preferred over the log likelihood since the estimated likelihoods increase when the number of parameters are increased. The AIC is calculated by weighting the likelihoods with penalities. The models wit least AIC if selected, and the acf plots of the squared estimated residuals are studied.

5.2 Fitted Models

Table 2: Fitting GARCH Model for Emerging Markets

	Saudi Arabia	Taiwan	Rep. of Korea	Mexico
		Mean Equation		
μ	0.0006512	0.00051635	0.00027175	0.0001943
		Variance Equation		
ω	0.0000048	0.00000459	0.0000028	0.000002
$\alpha 1$	0.081938	0.0513353	0.0994856	0.087112
$\alpha 2$	0.036509	0.0647675		
$\beta 1$	0.8429849	0.8373943	0.872423	0.886607

The μ captures the long term average volatility in the index returns.This is found to be quiet close to zero for all four emerging markets. This could be due the choice of measuring daily returns. The long run average return are found to be positive.

In case of Taiwan, all the estimated parameter were found to be significant at the 1% level. Excluding $\alpha 2$ the estimates of Saudi Arabia were also found to be significant at the 1% level. While the μ was found to be insignificant at the 1% level for Korea, all other estimated coefficients for Korea and Mexico were statistically significant at less than 1% levels.

The sum of the estimated ARCH and GARCH coefficients were used to determine the stability of the models. The stability estimates for Saudi Arabia, South Korea, Mexico and Taiwan are 0.961, 0.972,0.974 and 0.953 respectively. The models are found to be stable and the sum of the alphas and betas are less than one.

The estimated are significantly smaller than the beta coefficients. The capture the short run volatility in the markets. The fitted models suggest that the ARCH effects are the largest among Mexico and South Korea.This means that the shocks arising from Taiwan tends to have a smaller impact on their own market in comparison to South Korea.

The β estimates the long term conditional volatility. The volatility on average is about 80.00% across the emerging markets. This represents the mean reversion of the markets. Mexico appears to have the largest conditional volatility estimate of about 87%. This implies that the shocks are more persistent in Mexico relative to Taiwan.

Table 3: Fitting GARCH Model for Developed Markets

	USA	China	Japan	Canada	Hong Kong
		Mean Equation			
μ	0.000791	0.000053721	0.00066429	0.0003790	0.00025308
$\phi 1$	-0.05654420			0.05914574	
		Variance Equation			
ω	0.00000357	0.000001332	0.00000741	0.00000159	0.00000231
$\alpha 1$	0.17101189	0.067165114	0.12207815	0.1400892	0.05737944
$\beta 1$	0.8012597	0.926504039	0.83608981	0.8414840	0.92825776

The results of the ARMA-GARCH process has been summarized above for USA, China and Canada. The returns from Hong Kong and Japan did not have serial correlation. To model the dependence, AR orders are included and later dropped if found to be statistically insignificant, the objective is build parsimonious models that results in uncorrelated residual squares.

Excluding the average returns from Hong Kong and China, all estimated parameters were found to be statistically significant at the 5% level.While most of the stability estimates were found to be less than one, the sum of the arch and parameters were quiet close to one for China at about 0.994. The ARCH coefficients were also found to be significantly smaller that the GARCH estimates.

The volatility persistence was found to be the greatest for Hong Kong and China, this implies that the mean reversion is relatively slower for these economies. The short term volatility appears to be the greatest in the USA, followed by Canada.

6 Volatility and Causality

The analysis of volatility spillover begins with a plot of the estimated conditional volatilities. The Correlation matrix of the spillover suggests that the conditional variances are positively correlated for all countries but Korea and China. There appears to be a low degree of negative correlation between the volatility estimates of China and Korea. The is about 50% correlation in the contional variances of Hong Kong and Korea. Moderate Correlations are observed between USA and Mexico as well as Hong Kong and Taiwan. Correlation however does not imply causation. In order to establish causation between each emerging economy and their trade partners, a granger causality test is done.

	TAIWAN	KOREA	SAUDI ARABIA	MEXICO
CHINA	0.0520277	-0.03039085	0.06685639	0.02274781
USA	0.1094992	0.15846777	0.05977943	0.42034024
HONGKONG	0.4361616	0.49081860		
Japan		0.13599908		
Canada			0.55776616	

Table 4: Correlation Matrix

6.1 Taiwan-USA-China-Hong Kong

The plot below depicts the volatility patterns from 2010 to 2024 of Taiwan and it's trade partners, USA, China and Hong Kong. There appears to be a lagged correlation in the volatilities among the countries. It is also unclear as whether the volatility is transmitted from Taiwan or from other trade partners. The volatility trends mimic the pattern observed in the returns of these stocks. The conditional variances appear to be quiet high for China. This corresponds to the high beta coefficient as well.

The Granger causality test yields an exceedingly small p-value, indicating strong evidence against the null hypothesis. With the estimated p-value significantly below the conventional 5% threshold, it is evident that Taiwan exerts a Granger-causal influence on the volatility of the USA, China, and Hong Kong. Moreover,

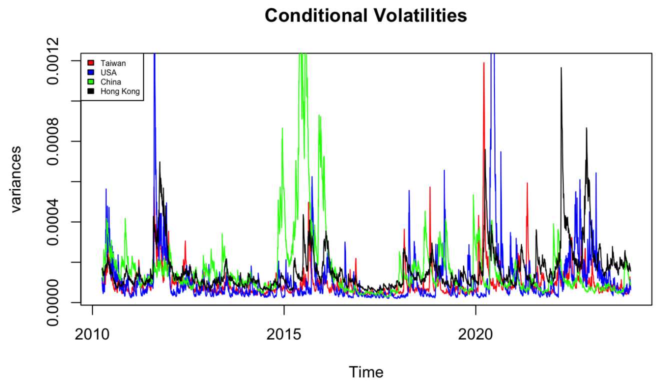


Figure 28: Plot of Conditional Variances from 2010 to 2024

the analysis reveals compelling evidence of instantaneous causation in volatility from Taiwan to its trade partners.

In essence, the findings suggest a directional relationship where past values of Taiwan's conditional volatility contain valuable predictive information for the current volatilities of these markets, even after accounting for their own past volatilities. This underscores Taiwan's role as a significant determinant of volatility dynamics within the interconnected financial landscape of the USA, China, and Hong Kong.

Table 5: Granger Causality Test Results for Taiwan

Granger Causality Test			
Null Hypothesis	F-Statistic	df	p-value
H_0: TAIWAN does not Granger-cause CHINA USA HONGKONG	3.2154	(21, 13452)	0.0000009111
Instantaneous	Chi-squared	df	p-value
H_0: No instantaneous causality between TAIWAN and CHINA USA HONGKONG	11.944	3	0.007578

The presence of instantaneous causation further accentuates the immediacy of Taiwan's impact on the volatility of its trading partners. This implies that fluctuations in Taiwan's financial markets have an immediate and discernible influence on the volatility levels observed in the USA, China, and Hong Kong, reflecting the interconnectedness and interdependence of global financial markets.

Overall, these findings underscore the importance of considering Taiwan's financial market dynamics when analyzing volatility patterns in the USA, China, and Hong Kong. They highlight the need for policymakers and investors to monitor developments in Taiwan's financial markets closely, as they can have significant implications for the broader global financial landscape.

6.2 Korea-USA-China-Hong Kong

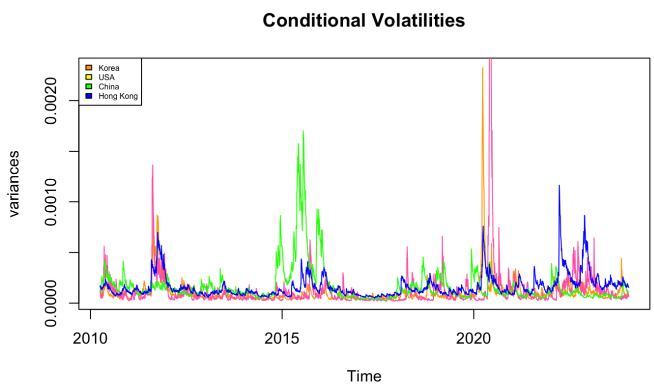


Figure 29: Plot of Conditional Variances from 2010 to 2024

While there are some differences in the magnitude and timing of volatility spikes across countries/markets, the overall patterns suggest that volatilities tend to move together. This could be due to global economic factors, financial market integration, or spillover effects.Based on the vertical scale, the conditional volatilities of Korea, the USA, and China appear to be higher compared to Hong Kong during the sample period.

Based on the Granger causality test results, we can conclude that Korea's con-

Table 6: Granger Causality Test Results for Korea

Granger Causality Test for Korea			
Null Hypothesis	F-Statistic	df	p-value
H_0: Korea does not Granger-cause China, USA, Hong Kong	6.1267	(21, 13452)	< 0.00000000000000022
Instantaneous	Chi-squared	df	p-value
H_0: No instantaneous causality between Korea and China, USA, Hong Kong	0.98363	3	0.8052

ditional volatility Granger-causes the conditional volatilities of China, the USA, and Hong Kong. In other words, past values of Korea's conditional volatility contain useful information for predicting the current values of the conditional volatilities of these other markets, even after accounting for their own past volatilities.

The second row presents the results of an instantaneous causality test, which examines whether there is a contemporaneous relationship between Korea's conditional volatility and the conditional volatilities of China, the USA, and Hong Kong.Given a p value greater than 5%, the null hypothesis cannot be rejected.

The Granger causality test results indicate that Korea's conditional volatility Granger-causes and has a lead-lag relationship with the conditional volatilities of China, the USA, and Hong Kong. Additionally, there is no evidence of instantaneous causality or a contemporaneous relationship between these volatilities.

6.3 Mexico-USA-China-Canada

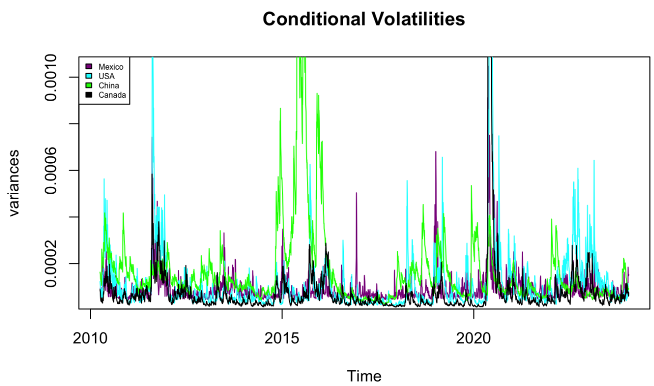


Figure 30: Plot of Conditional Variances from 2010 to 2024

There is a clear pattern of volatility clustering, where periods of high volatility tend to be followed by high volatility, and periods of low volatility tend to be followed by low volatility.While the magnitudes of these volatility spikes differ across markets, there is a noticeable co-movement and potential for volatility spillovers. This suggests that the markets are interconnected, and volatility shocks in one market may transmit to others due to factors such as globalization, economic integration, and common underlying drivers. Examining the relative volatility levels, China and Mexico appear to exhibit higher conditional volatilities compared to the United States and Canada during certain periods. However, these relative rankings may shift over time and across different market regimes or events.

According to the findings from the Granger causality test, it can be inferred that Mexico's conditional volatility serves as a predictive factor for the current values of conditional volatilities in China, the USA, and Canada. This suggests

Table 7: Granger Causality Test Results for Mexico

Granger Causality Test for Mexico			
Null Hypothesis	F-Statistic	df	p-value
H_0: Mexico does not Granger-cause China, USA, Canada	16.539	(48, 13272)	< 0.00000000000000022
Instantaneous	Chi-squared	df	p-value
H_0: No instantaneous causality between Mexico and China, USA, Canada	26.848	3	0.000006337

that utilizing historical data on Mexico's conditional volatility provides valuable insights for predicting the current volatilities of these markets, even when factoring in their own historical volatilities.

The results of an instantaneous causality test, investigates whether there exists an immediate relationship between Mexico's conditional volatility and the conditional volatilities of China, the USA, and Canada.The instantaneous causality test results indicate the rejection of the null hypothesis, which implies the absence of no instantaneous causality between Mexico's conditional volatility and the conditional volatilities of China, the USA, and Canada. This suggests the presence of a contemporaneous relationship or an instantaneous spillover effect among these volatilities.

6.4 Saudi Arabia-USA-China-Japan

It reveals a phenomenon of volatility clustering, where periods of both high and low volatility tend to endure. Notable spikes in volatility are evident around 2010, 2015, and 2020, possibly reflecting significant economic events or market turbulence. Although the magnitudes vary, there appears to be a degree of synchronized movement and potential transmission of volatility shocks across these markets, indicating interconnectedness. The levels of volatility differ, with China and Saudi Arabia displaying higher volatilities during certain periods. A significant change in volatility dynamics is observed around 2020, likely attributed to the COVID-19 pandemic's impact on global markets

The table presents the results of the Granger causality test conducted for Saudi Arabia, aiming to assess its causal relationship with the markets of China, the USA, and Japan. For the null hypothesis stating that Saudi Arabia does not Granger-cause these markets, the F-statistic is calculated at 0.77695, with degrees of freedom noted as (21, 13452), yielding a p-value of 0.7516. This indicates insufficient evidence to reject the null hypothesis, suggesting that Saudi Arabia may not significantly Granger-cause the volatilities of the mentioned markets.

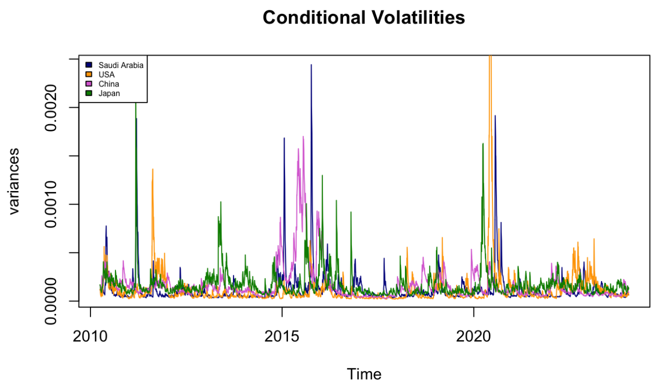


Figure 31: Plot of Conditional Variances from 2010 to 2024

Moreover, an instantaneous causality test is performed to explore the possibility of immediate relationships between Saudi Arabia and the markets of China, the USA, and Japan. The null hypothesis posits no instantaneous causality between Saudi Arabia and these markets. The chi-squared statistic for this hypothesis is computed as 0.50589, with 3 degrees of freedom, resulting in a p-value of 0.9176. This high p-value implies that there is no significant evidence to reject the null hypothesis, indicating the absence of instantaneous causality between Saudi Arabia and the volatilities of the mentioned markets.

In essence, based on these statistical tests, there is insufficient evidence to conclude that Saudi Arabia Granger-causes the volatilities of China, the USA, and Japan, nor is there evidence of an immediate causal relationship between Saudi Arabia and these markets. These findings suggest that the volatility dynamics of Saudi Arabia may not significantly influence or be influenced by the volatilities of these major markets. However, further analysis and consideration of additional factors may be necessary to fully understand the complex interactions and potential spillover effects among these markets.

Table 8: Granger Causality Test Results for Saudi Arabia

Granger Causality Test for Saudi Arabia			
Null Hypothesis	F-Statistic	df	p-value
H_0: Saudi Arabia does not Granger-cause China, USA, Japan	0.77695	(21, 13452)	0.7516
Instantaneous	Chi-squared	df	p-value
H_0: No instantaneous causality between Saudi Arabia and China, USA, Japan	0.50589	3	0.9176

7 Conclusion

8 Reference

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