Impact of United States Dollar Volatility Across Emerging and Developed Equity Markets

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Abstract

The paper seeks to assess the presence and impact of a unidirectional flow of volatility from the United States Dollar (USD) to five Developed and five Emerging Markets equity returns across the Global Financial Crisis (GFC) period. Basing its analysis on the Morgan Stanley Capital International (MSCI) equity returns indexes, the paper utilizes multivariate Dynamic Conditional Correlation (DCC) MV-GARCH processes to isolate the dynamic conditional correlations from the conditional variance component in order to highlight and rank these markets' sensitivity to the USD volatility. Generally, there is evidence of low asymmetric dynamic correlation between USD volatility and equity returns volatility from both markets. This implies that exchange rate and equity markets are informationally inefficient such that one market has some predictive power over the other. The bivariate correlation is greater among developed markets and lowest among emerging markets. The analysis indicates that South Africa in particular has the lowest bivariate conditional correlation with the USD compared to all other equity markets, thus proving to be a preferable diversification choice in times of global market uncertainty. These results have substantial implications for international portfolio managers and hedgers in their assessment of investment opportunities and asset diversification decisions across markets. Consequently, Investors can better comprehend how volatility between exchange rate and equity markets interlink overtime in order to forecast market behavior.

Keywords: Multivariate GARCH - Dynamic Conditional Correlation Model, Volatility Spillover, Exchange Rate market, Equity Markets

JEL classification L250, L100

1. Introduction

Volatility modeling is one area that has received considerable attention especially with regard to equity market and exchange rate volatility correlations. The internationalization of capital markets and homogenization of asset price movements across financial systems is one factor that has fueled interest in exchange rate volatility and its effect on stock market volatility. According to Katzke (2013), strong correlation of asset markets that go even beyond fundamental linkages tend to be rife

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during global economic uncertainty as a result of these interconnected within global financial systems and instantaneous information flow. The working theory has been that the increased globalization of financial markets contributes to the increase in volatility of financial systems since these systems have been shown to be susceptible to surprise shocks from other markets including exchange rate fluctuations.

Investors have over the years taken note of the fact that a trade-off exists between expected return and risk as a result of the inherent volatility in these markets. Understanding this risk-return trade-off is fundamental to investors as they endeavor to diversify their portfolios by investing in different asset classes which have low to negative correlations across equity markets. It is well documented that emerging equity markets are characterized by high volatility, as opposed to developed markets. This study looks at the intensity at which the US Dollar (USD) volatility in particular contributes to Emerging Markets (EM) and Developed Markets (DM) stock market returns' volatility. The findings can complement the emerging body of literature by establishing which among developed and emerging equity markets is mostly vulnerable to the USD volatility as the universal reserve currency.

Moreover, by relating USD volatility effect in EMs, to its volatility effect in DMs, the paper can assess whether the effects in these markets are driven by this common component or other macroeconomic or political factors. The results will enhance the systematic understanding of spillover activities between the US as a super power and the rest of the world. To capture this volatility spillover, the study employs Dynamic Conditional Correlation - Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCC MV-GARCH) modeling technic because of its capability to capture time-varying correlations in volatility. It finds that currency movements can have significant effects on investment returns volatility leading to the use of currency hedges to remove direct effects of exchange rate volatility. The paper concludes that evaluation of potential returns from either developed or emerging stock markets should take into account an analysis of the effects of currency trends on company earnings as this bare vital insight into global asset performance.

The remainder of the paper is organized as follows. Section 2 highlights relevant literature to both exchange rate and equity market volatility among EM and DM countries. Section 3 breaks down the data composition of the dataset used in the study and the associated quality control measures employed to ensure accuracy and appropriateness of the intended analysis. Section 4 details the methodology adopted for analysis of the subject at hand while Section 5 presents the results of the estimated models. The last Section presents a summary and conclusion of the study.

2. Theoretical Overview

In theory, investment decisions are governed by Portfolio theory which dictates that an investor should firstly be guided by the desire to maximize expected return while minimizing risk. These strategies are however at loggerheads since riskier assets usually bare higher returns whereas less risky assets bare low returns. The direction of correlation between any two assets also has bearing on their riskiness. Negative correlation between risky assets reduces portfolio volatility since a negative return can eventually be accompanied by a positive return hence a reduction in the portfolio's volatility whereas a positive correlation between risky assets increases portfolio volatility (Ruppert & Matteson, 2015). Since investors demand a reward for bearing the risk they usually opt for volatile assets in expectation of the associated higher returns, thus investors are drawn towards the more volatile markets. Emerging Markets have for the longest time been theorized to be the more volatile market and a common destination for international portfolio investors looking to obtain diversification rewards better than in DMs (Hung, 2019). The latter has been proven by the surge of investors to EMs in recent years as increased number of high return shares were issued, reflected by the growing weight of EMs in the MSCI all country index composition (Blitz *et al.*, 2013). The dispersion of volatility among EM countries also tends to be higher than that found among DM countries whereas cross correlation among EMs is small.

According to Bekaert & Harvey (1997), this only forms part of the distinguishing factors between developed and emerging markets. He explains that EMs also have high average returns, low market return correlations with developed markets and more predictable returns (Bekaert & Harvey, 1997). DeSantis & Imrohoroglu (1994) are also off the view that EMs rather than DMs are characterized by high kurtosis as a result of returns that varyfrom either very high or very low. Shin (2005) also emphasizes that the degree of integration between EMs and DMs plays an important role in determining spillover effects between them since a shock to the world market returns affects all countries with any form of covariance with it. The source of volatility may relate to asset diversification or concentration, equity market development, macroeconomic or political influences (Bekaert & Harvey, 1997). For purposes of this paper, the focus is on exchange rate volatility, as a source of volatility with particular interest on US dollar volatility because of its position as the global reserve currency and dominance of the US financial market. An appreciation of the domestic currency against the dollar has an influence on international investors because their returns increase whereas a depreciation of the local currency against the USD results in a reduction of their returns. According to Bahmani-Oskooee & Sohrabian (1992), the inverse relationship between domestic (foreign) assets and foreign (domestic) interest rates and the positive relationship between domestic (foreign) assets and domestic (foreign) interest rates solidifies the role of exchange rates in balancing asset demand and supply.

Lim & Sek (2014) study Volatility in EMs and concludes that exchange rate volatility does affect equity market returns. Adjasi *et al.* (2008) also share the same sentiment and find an inverse relationship between exchange rate volatility and equity market returns. They note that an increase in volatility of the local currency exchange value results in financial volatility and subsequent increase in investor uncertainty. Mcgibany & Nourzad (1995) reiterate that when faced with such an option, local investors are motivated to substitute assets they believe are safe for riskier. They however note that Investors tend to hedge against their own currency depreciation, or even seek to profit off other currencies' appreciation by holding assets linked to it in order to cushion against volatility risk. Kanas (2000) & Morales (2008) study on volatility spillover from exchange rate markets to equity markets in USA, UK, Canada, Japan, Germany, France, Czech Republic, Hungary, Poland and Slovakia using bivariate Exponential-GARCH (EGARCH) model on daily data finds insignificant volatility spillover from exchange rate to equity markets. This they explained could be a result of a number of reasons. Firstly, the use of daily data in thier study couldn't capture effects of trade flows on exchange rate changes, secondly, the counteractive effect of positive exchange rate volatility on equity markets for one firm can be offset by a negative effect for others resulting in weak exchange rate effect, and lastly the reason could be the fact that volatility spillovers can be counteracted by the use of exchange rate risk hedges such as futures, forwards and currency option (Kanas, 2000 & @morales2008). Raghavan & Dark (2008) however find a significant unidirectional volatility spillover from the USD/AUD exchange rates to the Australian All Ordinaries Index (AOI) using daily data from 2 January 1995 to 31 December 2004. However, Mishra *et al.* (2007) & Kumar (2013) use the bivariate EGARCH model in India, Brazil, and South Africa and find a significant bi-directional volatility spillover between stock and foreign exchange markets proving the existence of information transmission and integration between the two markets. Moreover,Chkili & Nguyen (2014) use Markov-Switching EGARCH model on weekly data to find a significant impact of exchange rate changes on stock market volatility in Hong Kong, Singapore, Malaysia and Mexico. They also conclude that the relationship between exchange rate and equity markets in EMs dependent on either low volatility or high volatility regimes.

Findings from the various studies differ from country to country conditional on the methodology and time span of data utilized. It is therefore prudent to study the effects of exchange rate volatility on equity market returns with particular interest on comparing samples from EMs and DMs within the same context, using updated methodologies, time span and most importantly using recent data. Therefore the importance of modeling volatility within financial markets has taken center stage since the introduction of ARCH models by Engle (1982) in his seminal paper (Katzke, 2013; Silvennoinen & Teräsvirta, 2009). Silvennoinen & Teräsvirta (2009) show that the initial works of authors like Bollerslev *et al.* (1994) & Shephard (1996) focused on univariate models hence extending such works to the multivariate dimension is also vital. Ruppert & Matteson (2015) show that GARCH models on the other hand have gained popularity in econometrics because of their ability to randomly vary volatility in time series data. These models are best known to model both the conditional heteroskedasticity and the heavy-tailed distributions of equity markets data.

3. Data

The study uses value-weighted equity market indices for ten major equity markets around the world. These are Egypt, Taiwan, India, Brazil, South Africa, Japan, United Kingdom, France, Canada and Switzerland. The data is acquired from the Morgan Stanley Capital International (MSCI) and Bloomberg databases for the period starting in 2003 to 2018 (15-year period to capture the impact of the Global Financial Crisis (GFC)). This sample period enables the research to examine the effect of US dollar volatility on EM-DM equity markets during both bad and good times. The GFC is an appropriate example of bad times since both Developed countries and Emerging countries' equity markets experienced a downturn.

Under the MSCI taxonomy, Egypt, Taiwan, India, Brazil, South Africa, are categorised as "EMs" while the otherabovementioned countries are categorised as "DMs". Bloomberg on the other hand provided the Bloomberg Dollar Spot Index(BBDXY) which is an Index that tracks the performance of a basket of 10 leading global currencies against the United states dollar. All these indices are widely used in equity market research on volatility transmission because of the degree of comparability they allow. Weekly data is analysed as opposed to monthly data in order to provide sufficient observation required by the GARCH model in the absence of short term correlations due to the noise that is usually found in daily data. Higher frequency data like daily data tends to be more volatile and has more noise that might not correspond to long run fundamental behaviour. Monthly data on the other hand does not give sufficient information for estimation since monthly returns are longer horizon returns which can musk momentary responses to innovations which may only last for days. The stock value indexes are expressed in US dollars to avoid exchange rates differences. For further analysis, the continuously compounded daily returns are calculated by taking the log difference of each listed company as follows;

$$r_{i,t} = ln(\frac{P_{i,t}}{P_{i,t-1}}) * 100$$

Where $r_{i,t}$ represents the natural logarithm of weekly stock returns from selected DM and EM country indices with $P_{i,t}$ as the closing price of the market index, i, at time t.

Table 6.1 outlines all the EM and DM countries and their respective Tickers as used by the MSCI and Bloomberg databases. Table 3.1 on the other hand presents the Summary Statistics for all the Tickers used for analysis. The normality test using the Jarque–Bera test the for weekly returns is rejected as expected. In addition, both the skewness and excess kurtosis statistics also indicate that the distributions of all the Indices are non-normal. That is, the kurtosis is greater than zero which represents a normal distribution. The excess kurtosis shows that the distribution has heavy tails and as such is a leptokurtic distribution common in financial time series data. The returns as seen in table 3.1 are substantially negatively skewed. The BBDXY indice displays the highest mean whereas the MXJP displays the lowest mean. The graphical representation of all the indices can be viewed on figure 6.1 in the Appendix. All the equity markets were substantially affected by the 2008 Global Financial Crisis as seen by the decline in returns during the period. The recurrence of very high and very low returns observed particularly in the sampled emerging countries indicates the presence of leptokurtosis. The overall graphicall presentation in figure 6.1 indicate periods of volatility clustering highlighting the presence of serial heteroskedasticity.

In order to control for any remaining serial heteroskedasticity in the series and explore the conditional covariance structure for further analysis, the next section shows the generalization of the Univariate Garch(1,1) Model to the multivariate domain in order to conduct multivariate volatility modeling.

	group1	mean	sd	median	trimmed	min	max	skew	kurtosis	se
dlogret1	BBDXY	0.00	0.01	0.00	0.00	-0.04	0.04	0.26	1.77	0.00
dlogret2	MXBR	0.00	0.05	0.01	0.00	-0.33	0.26	-0.45	5.92	0.00
dlogret3	MXCA	0.00	0.03	0.00	0.00	-0.26	0.18	-1.17	10.69	0.00
dlogret4	MXCH	0.00	0.03	0.00	0.00	-0.25	0.13	-1.53	14.67	0.00
dlogret5	MXEG	0.00	0.04	0.00	0.00	-0.37	0.15	-1.45	9.59	0.00
dlogret6	MXFR	0.00	0.03	0.00	0.00	-0.27	0.14	-1.12	8.10	0.00
dlogret7	MXGB	0.00	0.03	0.00	0.00	-0.28	0.17	-1.35	13.84	0.00
dlogret8	MXIN	0.00	0.04	0.00	0.00	-0.22	0.18	-0.45	3.82	0.00
dlogret9	MXJP	0.00	0.02	0.00	0.00	-0.16	0.09	-0.64	3.61	0.00
dlogret10	MXZA	0.00	0.04	0.00	0.00	-0.20	0.29	0.09	4.43	0.00
dlogret11	TAMSCI	0.00	0.03	0.00	0.00	-0.12	0.10	-0.52	1.53	0.00

Table 3.1: Descriptive Statistics Table

4. Methodology

In order to analyze the transmission of volatility from the US dollar to both EM and DM equity markets, direct time-varying conditional correlations between the different markets are modeled using Dynamic Conditional Correlation (DCC) MV-GARCH models as suggested by Engle (2002). These models are preferred due to their ability to accommodate volatility clustering. Tsay (2013), Engle (2002) & Katzke (2020) emphasize that these models are preferable due to their applicability in various situations where their flexibility enables specifying Univariate GARCH Models and lead to gains in parsimony as they can be estimated either with univariate or two step methods based on the likelihood function to keep track of the time evolution of conditional correlations regardless of the number of assets. The first step is to obtain the GARCH estimates for the univariate volatility estimates for each returns series. The empirical analysis is undertaken considering a stochastic process r_{it} of a continuously compounded weekly returns as shown below;

$$r_{it} = \mu_{i,t} + \varepsilon_{i,t} \tag{4.1}$$

Where $\mu_{i,t}$ is the conditional mean and $\epsilon_{i,t}$ is the conditionally heteroskedastic error series.ϵ_{it} is expressed as $\epsilon_{it} = \sqrt{h}_{it}\eta_{it}$ and can be used to fit the univariate GARCH process for each series to obtain the conditional variance used to standardise the residuals. This is expressed as;

$$\eta_{it} = \epsilon_{it}/\sqrt{h}_{it} \quad with \quad \epsilon_{it} \sim N(0, H_t) \quad and \quad \eta_{it} \sim N(0, I) \tag{4.2}$$

On a multivariate scale, according to Engle (2002) we generalise Bollerslev's (1990) Constant Conditional Correlation (CCC) estimator and use the standardised residuals from 4.2 above to construct time varying conditional correlations whereby the dynamic correlation model H_t is assumed to be;

$$H_t = D_t.R_t.D_t. \tag{4.3}$$

Equation 4.3 splits the Variance-Covariance matrix into identical diagonal matrices D_t and refers to time varying conditional correlations matrix R_t. The diagonal matrices are defined as;

$$D_t = diag(\sqrt{h}_{it}). \tag{4.4}$$

Then we define the dynamic conditional correlation structure. This is shown in 4.5 below;

$$\begin{aligned} Q_{ij,t} &= \bar{Q} + \alpha\left(z_{t-1}z'_{t-1} - \bar{Q}\right) + \beta\left(Q_{ij,t-1} - \bar{Q}\right) \\ &= (1-\alpha-\beta)\bar{Q} + \alpha z_{t-1}z'_{t-1} + \beta Q_{ij,t-1} \end{aligned} \tag{4.5}$$

$Q_{ij,t}$ is the unconditional variance between series i and j. $\bar{Q}$ is the unconditional covarience between univariate series estimated in step 1. The non-negative parameters are represented by α and β and they must satisfy $\alpha + \beta < 1$ and each is < 0 so that the model is mean reverting Engle (2002). The paper however takes note of the fact that this could possibly represent a drawback of the DCC models since the α and β being scalars could mean that all the conditional correlations will obey the same dynamics which are necessary to ensure that R_t is positive definite as Bauwens *et al.* (2006) suggests. Mishra *et al.* (2007) also suggests that GARCH models do not differentiate reaction of volatility from either positive and negative shocks. He however argues that negative shock to financial time series could cause a rise in volatility that is greater than a positive shock of the same magnitude.

Employing Equation 4.5, the dynamic time-varying conditional correlation matrix R_t is estimated as;

$$R_t = diag(Q_t)^{-1/2} Q_t . diag(Q_t)^{-1/2}. \tag{4.6}$$

Equation 4.6 allows us to fit an R_t matrix with the following elements;

$$R_t = \rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} . q_{jj,t}}} \tag{4.7}$$

This results in a DCC model formulated as in 4.8, which has the assumption of normality that produces a likehood estimator as opposed to a Quasi-maximum Likelood estimator and also includes the assumption that each asset in the series follows a univariate GARCH process (Engle, 2002).

$$\begin{aligned}
\varepsilon_t &\sim N(0, D_t.R_t.D_t) \\
D_t^2 &\sim \text{Univariate GARCH(1,1) processes } \forall \text{ (i,j), i} \neq \text{j} \\
z_t &= D_t^{-1}.\varepsilon_t \\
Q_t &= Q(1-\alpha-\beta) + \alpha(z_t' z_t) + \beta(Q_{t-1}) \\
R_t &= Diag(Q_t^{-1}).Q_t.Diag({Q_t}^{-1})
\end{aligned} \tag{4.8}$$

5. Results

This section presents the main empirical findings on measuring volatility spillover between the USD, EM and DM equity markets. It uses the DCC-GARCH model results to highlight time-varying conditional correlations between the dollar and these markets. This approach is two-fold. Firstly, the standard Univariate Garch (1,1) was modeled to give the estimated volatility series (σ or h_t series{ used interchangeably in the analysis}), whose standardized residuals are then utilized to estimate the Dynamic Conditional Correlations. The series was first tested for conditional heteroskedasticity using the Multivariate Generalization of the Lagrange Multiplier (LM) test (MARCH test) of Engle (1982). The MARCH test as detailed below shows that all the MV portmanteau tests rejected the null hypothesis of no conditional heteroskedasticity as all the four test statistics utilized have p-values of zero , affirming the choice to use the chosen MV-GARCH model. As expected the test confirmed the presence of conditional heteroskedasticity in the weekly log return series which is not surprising since financial time series data is known to have conditional heteroskedasticity. This shows that the conditional covariance of the sampled multivariate series is time dependent.

```
## Q(m) of squared series(LM test):
## Test statistic:  1597.899  p-value:  0
## Rank-based Test:
## Test statistic:  736.862  p-value:  0
## Q_k(m) of squared series:
## Test statistic:  7212.863  p-value:  0
## Robust Test(5%) :  2234.973  p-value:  0
```

The resultant volatility estimates for each series are shown in figure 6.2. The figure highlights high correlation between the returns volatility of EM and DM equity markets which is even more apparent during the GFC period as the volatility of all returns spiked. This can be seen as a possible indication of a global systematic risk factor. It is evident from 6.2 that EMs have the most volatile returns compare to DMs throughout the sample period. Among this, MXEG is the most volatile, followed by MXBR indicating a significant and distinct volatility effect within EMs that keeps growing overtime. The BBDXY is the least volatile but among the return series the MXCA and MXGB are among the least volatile. Overall the Univariate Garch (1,1) model highlights the existence of a consistent and similar risk-return relationship among EMs and DMs. The volatility in all returns appears to have increased in the latter part of the sample period with more dramatic swings beyond 2015. Generally, we find strong evidence of time-varying volatility. Particularly, there is volatility clustering in the sampled EMs similar to that evidenced in most developed financial markets making the MV-GARCH processes the most appropriated to be applied.

As mentioned above, the second step is then to use the standardized residuals obtained from the estimated Univariate Garch Model to estimate the time-varying DCC which provides a cleaner noise reduced version of the dynamic co-movements between the US dollar and EM-DM returns. Figure 6.3 shows how the bivariate dynamic/time varying conditional correlation between the USD and equity returns change overtime. Looking at the USD and MSCI index pairs in the figure we can see that the USD average correlation with the equity market returns is relatively low. Moreover, these volatility effects driven by the USD volatility can be ranked to reflect the least and most sensitive markets to the USD volatility. It is apparent from 6.3 that France followed by the United Kingdom and Japan represent the most sensitive DM equity returns to USD volatility. The volatility effect represents a unidirectional spillover of the USD volatility to these markets whose effect differs according to the individual market development and degree of market integration. One explanation for the large effect in these markets is the high use of the USD in commercial and financial transactions thus increasing their foreign exchange risk premium. Most of the EMs as portrayed in figure 6.3 seem to be less sensitive to the USD volatility whereby India, Egypt and South Africa are ranked lowest. This can be a result of the individual characteristics of the EM countries. Interestingly there is still a sharp decline in the correlations during the GFC indicating a significant volatility spillover to all equity markets during the period.

6. Conclusion

The paper examined the effect of U.S. dollar exchange rate on stock market volatility. The sample period chosen contains periods of small and large fluctuations such as the GFC which serves as an opportunity to study the volatility effect on market behavior in both pre and post crisis environments. The results highlight that heightened global uncertainty during such periods amplifies the co-movement between equity & exchange rate markets' volatility across both developed and emerging markets thus dampening investors' ability and desire to diversify their portfolios. By relating the volatility effect in these markets we are able to assess and differentiate whether the co-movement effects are a result of a common factor or various macroeconomic factors regardless of the GFC having proven to be a common shock across the board. We can conclude that there is significant evidence of low time varying correlations between the USD and Equity returns. This implies that exchange rate and equity markets are informationally inefficient such that one market has some predictive power over the other. These results have substantial implications for international portfolio managers, hedgers, individual and institutional investors in the assessment of investment and asset diversification decisions across markets. As a result Investors can better comprehend how volatility between exchange rate and equity markets interlink overtime in order to forecast market behavior. Generally, the findings indicate a unidirectional spillover in dollar volatility from the US to other markets whose impact differs according to market development.

More importantly, the results show that investors may need to diversify their investment portfolios and hedge against currency risk to maximize returns and avoid the volatility risk that exchange rate markets pose to equity markets. Specifically, international investors who have a large portion of USD traded assets would need to hedge the USD-local currency exchange rate so that they lock in the current exchange rate rather than be subjected to future volatility. This will likely have a positive effect on the domestic asset returns through decreased volatility and increased predictability. Some emerging markets in particular still lack the requisite market development equipped with hedging instruments that can mitigate potential exchange rate risk exposure resulting in positive correlation between the exchange rate volatility and equity markets volatility. However, EMs offer international investors with diversification opportunities as evidenced by low correlations with USD volatility as compared to DMs. Investors with a long time horizon and high tolerance for the volatility in emerging markets can expect returns well in excess of DMs' equities returns in the long run. In particular, the findings show South Africa to have the lowest bivariate conditional correlation with the USD amongst all the markets which presents it as an investment haven for international portfolio managers looking for assets with least co-movement characteristics.

As an avenue for future research, different measures of volatility such as the VIX (measure of market variance/ fear index) can be explored to see if the same bivariate conditional correlations exist between Exchange rate market and equity markets in South Africa specifically as has been evidenced with the GARCH derived USD volatility measure.

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Appendix A

6.1. Returns Description Table

	Ticker	Description
1	MXBR	Brazil
2	MXCA	Canada
3	MXCH	Switzerland
4	MXFR	France
5	MXGB	United Kingdom
6	MXIN	India
7	MXJP	Japan
8	MXZA	South Africa
9	TAMSCI	Taiwan
10	MXEG	Egypt
11	BBDXY	Bloomberg US Dollar Spot Index

Table 6.1: Returns description Table

6.2. MSCI Daily Returns Series

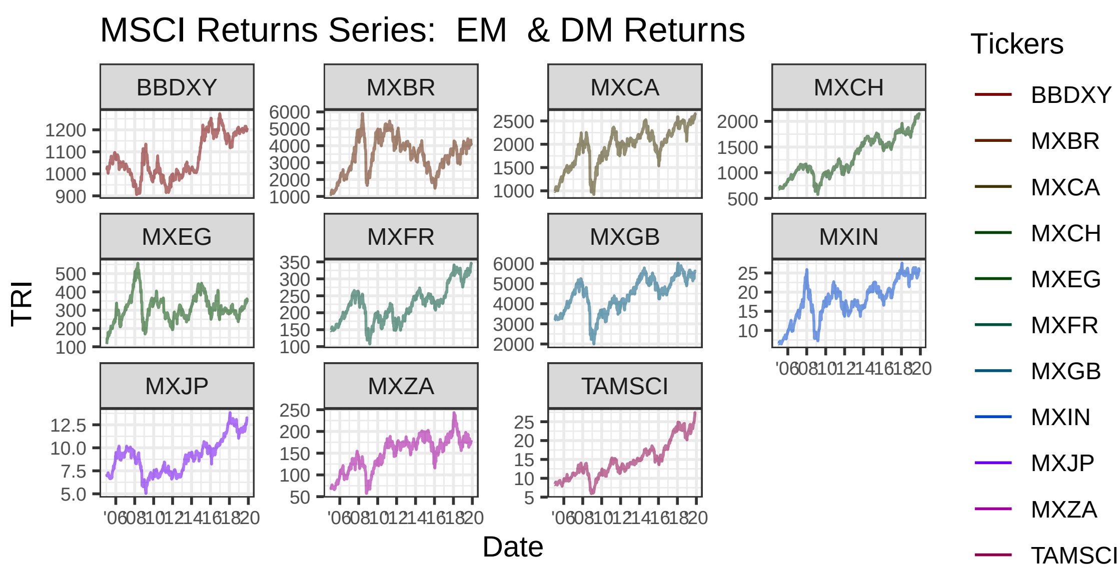

Figure 6.1: MSCI Returns

Apendix B

6.3. Individual Standard Univariate GARCH(1,1) model

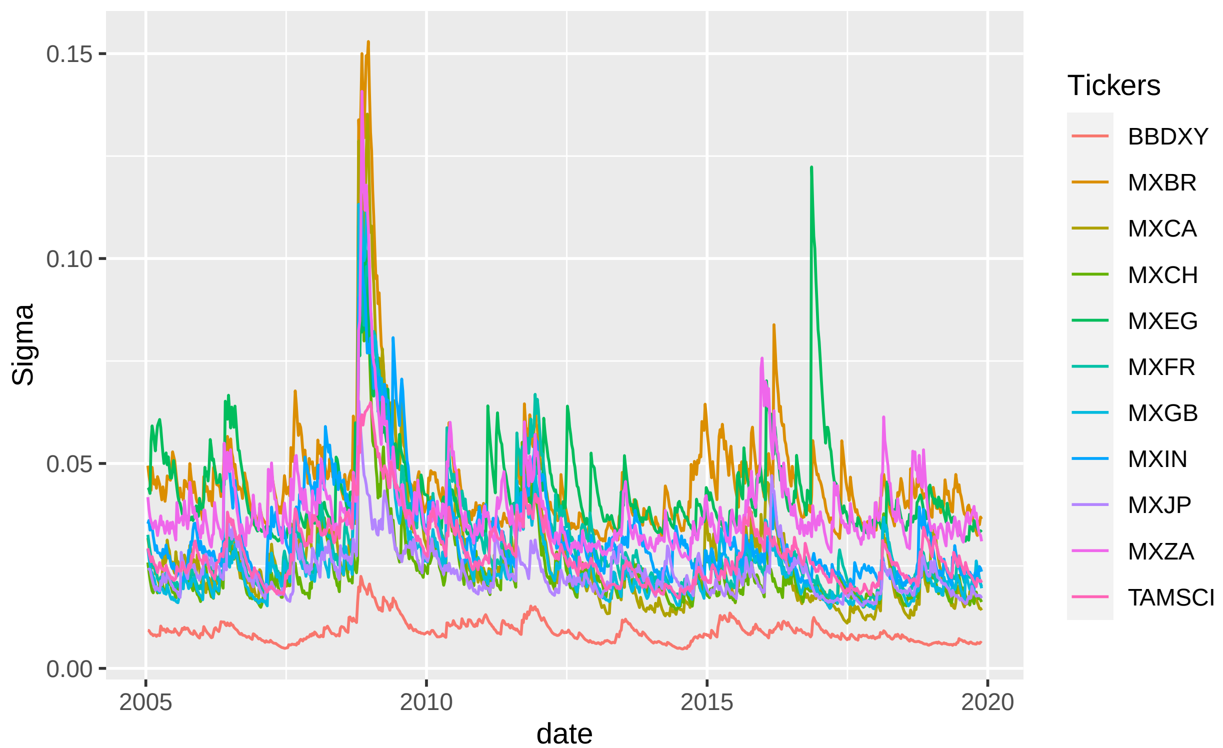

Figure 6.2: Series Volatility

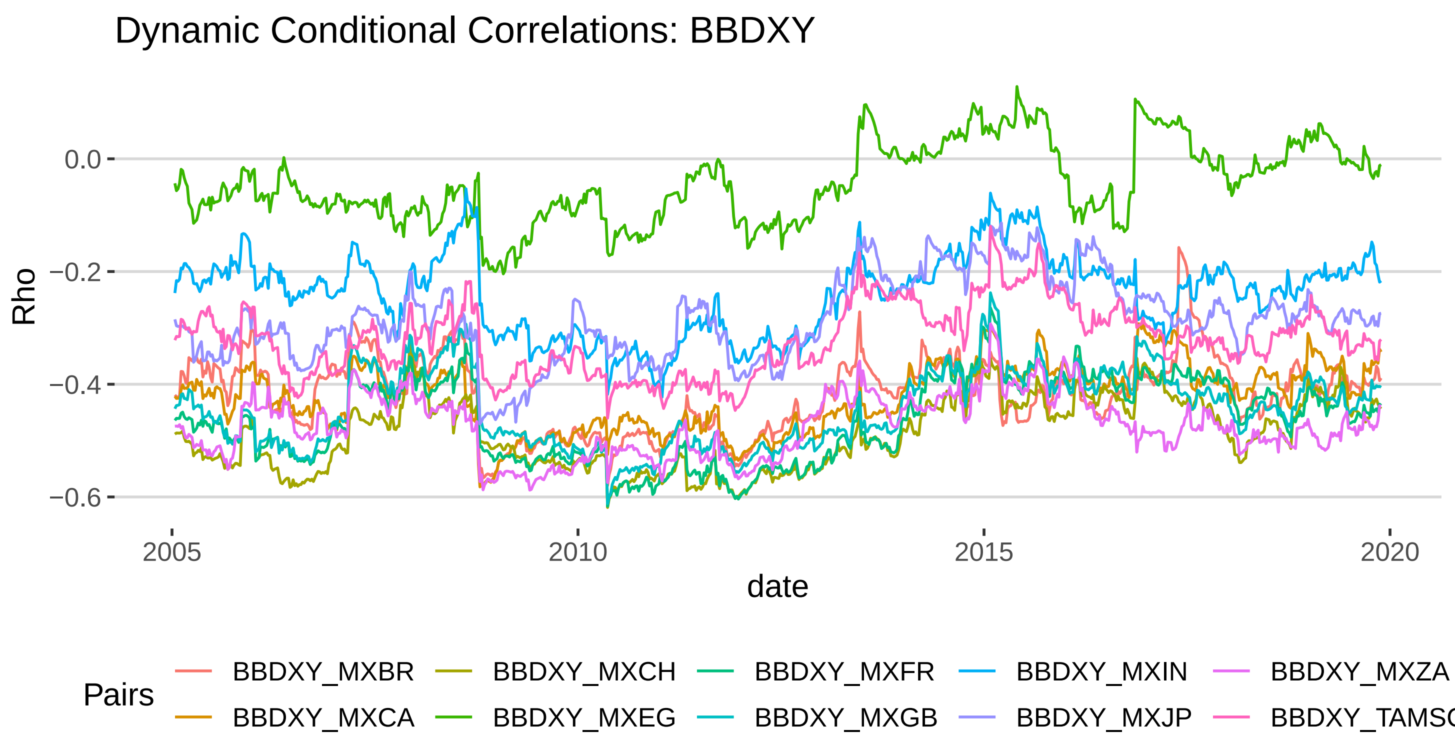

Figure 6.3: Series Volatility