Volatility Spillover between Developed and Developing Countries: The global Foreign Exchange Market's Channel

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Abstract

In this paper, we investigate the "statics and dynamics" return and volatility spillovers transmission across developed and developing countries. Quoted against the U.S. dollar, we study twenty-three global currencies over 2005 – 2016. Focusing on the spillover index methodology, the generalised VAR framework is employed. Our findings indicate no evidence of bi-directional return and volatility spillovers between developed and developing countries. However, a unidirectional volatility spillover from developed to developing countries is highlighted. Furthermore, our findings document significant bi-directional volatility spillovers within the European region (Eurozone and non-Eurozone currencies) with the British Pound (GBP) and the Euro (EUR) as the most significant transmitters of volatility. The findings reiterate the prominence of volatility spillovers to financial regulators.

JEL Codes: G01, G1, F3

Keywords: Foreign Exchange Market, Volatility Spillover, Return Spillover, VAR Framework, Variance Decomposition, Financial Crisis, Financial Interdependence

1. Introduction

The increasing financial interdependence, particularly during the current era of global economic events and financial turbulence has prompted considerable interest of market participants and academic research. While much attention has been paid to the magnitude of return and volatility spillover across global stock markets, little is known about the foreign exchange channel. In particular, the foreign exchange markets' channel between developed and developing countries. Some studies of this kind investigate the return co-movements and volatility spillover, primarily across the developed countries. Others, considered the regional spillovers transmission and produced insignificant results.

However, given the trillions of dollars of exchange rate trading in international financial markets; it is important to fully understand and investigate in greater depth the potential spillovers of international currencies. This is an important aspect that is taken into serious account from the investors for the formation of their position and portfolios. Before the recent financial turmoil, the contribution of the foreign exchange market's spillover channel to the global financial instability, for some, appeared to be less worrisome. Whereas, in fact, the behaviour of the stock prices (which extensively studied) mainly explained by volatilities in the foreign exchange market (Kim, 2003).

Thus, in this paper, we provide new insights to the incomplete investigation of the global intra-foreign exchange market's spillover channel. Our key question is whether the effect of return and volatility spillovers is bidirectional between developed and developing countries. This is because the recent financial crisis which originated in major financial hubs in developed countries, primarily in the U.S., that developing countries are not responsible for; nevertheless, they seriously affected by it. To study the return and volatility spillover transmission, we model the daily spot exchange rates for 23 global currencies, including the seven most-traded globally.² In particular, we adopt the generalised vector autoregressive (VAR) approach focusing on the variance decomposition of Diebold and Yilmaz (2009). The innovative feature of this approach besides being rigorous it allows the aggregation of valuable information across-markets into a single spillover index. The unique structure of the spillover index is designed to unleash an in-depth analysis of the negative spillovers' transmission across-markets, i.e., how a shock in a particular market is due to exogenous/endogenous shocks to other markets.

Since the financial crises are almost difficult to predict; nevertheless, it is important to identify fluctuations in volatility over different time period. Thus, we examine the time-varying net volatility spillover using the autoregressive conditional

¹ See, for example (Andersen et al., 2001; Pérez-Rodrìguez 2006; Boero et al., 2011; and Rajhans and Jain (2015).

² According to the BIS (2013), the USD, EUR, GBP, AUD, CAD, JPY and the CHF are the most traded globally, account for almost 90 per cent of the global foreign exchange turnover.

heteroskedasticity (ARCH) model. The time-varying volatility identifies the specific point of significant shifts in the volatility spillover during the years of our sample (2005 – 2016). We provide evidence of significant volatility clustering during the 2008 financial crisis. The ARCH model, which is first introduced by Engle (1982) is widely used in the literature³ for it is ability to capture persistence in time-varying volatility based on squared returns. And most importantly, to investigate the nature of the net volatility and net pairwise spillover effects, we implement (Diebold and Yilmaz, 2012) methodology. By doing so, we are able to show the difference between the amount of the gross volatility shocks within our sample that transmitted to and received from developed and the developing countries. To enhance the reliability of the findings, we provide evidence in different dimensions (using a sample of twenty-three global currencies over 2005-2016. The first is the static analysis approach, which provides results in the form of spillover tables. The second is the dynamic analysis, which yields the spillover plots. Third, is the time-varying net volatility results, which we provide in the form of figures. Finally, the net volatility and net pairwise spillover effects.

Overall, this paper is the first (to our knowledge) to document the transmission of returns and volatility spillover between developed and the developing countries. The analysis is based on a large daily spot exchange rates' dataset covers a long period pre and post the most recent events in the global economy. In particular, the paper provides results based on extensive empirical analyses such as the spillover index (both static and dynamic analyses), time-varying net volatility, net volatility and net pairwise volatility effects.

Guided by the empirical approach described above, the main findings indicate that no evidence of bidirectional volatility spillovers between developed and developing countries. Although, unsurprisingly, the results highlight evidence of unidirectional volatility spillovers pouring from developed to developing countries. In particular, the volatility spillovers from developed to the developing countries seem to be specifically strong following the collapse of Lehman Brothers in 2008. Another curious outcome of the findings is that developed countries are the most receiver and transmitter of volatility spillover, dominated by the British pound, Australian dollar, and the euro, whereas developing countries are a net receiver of volatility spillover. The findings, therefore, indicate that the currency crisis tends to be regional (Glick and Rose 1998; Yarovaya and others 2016).

Meanwhile, in light of the recent financial crisis, the analytical results demonstrate that the cross-country spillovers activities between developed and developing countries are insignificant, while the financial risk propagated during the recent financial crisis engulfed the global economy. That being said, because of the recent financial markets' development, for instance, financial engineering, (collateral debt obligation, credit default swap and derivative securities) financial risks triggered

³ See for example, Bollerslev et al. (1994), Kaur (2004), and Basher et al. (2007).

different means of spreading across the global economy, which still needs to be discovered, understood and spoken appropriately.

The rest of this paper is organised as follows: Section 2 discusses some critical arguments of related literature. Section 3 then introduces the data used in the analysis and the empirical methodology applied in section 4. In section 5, we provide empirical results, including the robustness and some descriptive statistics. Section 6 discusses the time-varying volatility. Section 7 introduces the net spillovers and net pairwise volatility spillovers. Section 8 concludes.

2. Related Literature

This brief review of the literature is focused on the foreign exchange market's spillover channel, which is one of the most intensely debated issues in recent literature. However, the significance of the foreign exchange market's spillover channel to the financial markets' stability acknowledged three decades ago. For example, Engle et al. (1990) established the first thread-tying efforts of the intra-day exchange rate's volatility spillover within one country (heat waves)4 and across-borders (meteor shower) 5. In this paper, the authors provide evidence of transmitted volatility spillovers from one market to another. This opening up, particularly after the recent financial crisis, amplified the importance of the spillover channels in the stock and the foreign exchange markets. This is due to the repercussions of the shocking types of financial risks stemming from the interconnected nature of the financial markets. Thus, there is growing evidence in the literature, which supports the association of return and volatility spillovers with global economic events and financial crises. (See, Diebold and Yilamz 2009; Beirne et al. 2009; Yilamz 2009; Gebka 2012; Jung and Maderitsch 2014; Ghosh 2014; Choudhry and Jayasekera 2014; Antonakakis et al. 2015; and Mozumder et al. 2015, for reviews).

Also, the recent financial crisis demonstrated the severity of the cross-market volatility spillovers, which transmitted across countries mainly through the stock and foreign exchange markets' channels. (see Fedorova and Saleem 2009; Mohanty et al. 2011; Maghyereh and Awartani 2013; Jouini 2013; Shinagawa 2014; Do et al. 2015 for reviews). Another important feature of the foreign exchange spillover channel that its effect act differently during, before and after the economic events and financial crises episodes. For example, based on VAR models, Diebold and Yilamz (2009) examined nineteen⁶ global equity markets from 1990s to 2009. They find striking evidence that return spillover displays slightly increasing trend but no bursts, while, volatility

⁴ The "heat waves" is a hypothesis indicates that a volatility in one market may continue in the same market next day

⁵ However, the "meteor shower" is a phenomenon implies that a volatility in one market can spillover to another market

⁶ Seven developed stock markets (in the US, UK, France, Germany, Hong Kong, Japan and Australia) and twelve emerging markets (Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey).

spillover displays no trend but strong bursts associated with crises events. In addition, the effect of return and volatility spillover may extend to the business cycle mechanism. Several studies (Imbs 2004; Eickmeier 2007; Imbs 2010; and Claessens et al. 2011 for reviews) argue that volatility spillover inflicts business cycle synchronisation between countries through different channels. These channels mainly include the exchange rate, confidence⁷; trade; and the financial integration channel. Antonakakis et al. (2015) suggest that the spillover effect could also be transmitted through business cycle across countries.

A number of studies attempted to empirically analyse the exchange rate comovements and volatility spillover across countries. In particular, the financial transmission between the euro (EUR), British pound (GBP), Australian dollar (AUD), Swiss franc (CHF), and the Japanese yen vis-á-vis the U.S. dollar. For instance, Boero et al. (2011), Rajhans and Jain (2015) found high correlation between the euro and British pound against the U.S. dollar and that the British pound is a net receiver. Nikkinen et al. (2006) study the future expected volatility linkages among major European currencies (the euro, British pound and the Swiss franc) against the U.S. dollar. They find future volatility linkages between the major currencies and that the British pound and the Swiss franc are significantly affected by the implied volatility of the euro. Boero et al. (2011) found an increase in co-movements between the euro and the British pound after the introduction of the euro compared to the pre-euro era. A different perspective is offered by Antonakakis (2012), using VAR model, the author finds significant return co-movements and volatility spillover between major exchange rates before the introduction of euro and lower during the post-euro periods.

The previously discussed papers establish the evidence of return co-movements and volatility spillover across developed countries' exchange rates. It is also important to examine the behaviour of asset return and volatility spillover of the foreign exchange markets between developed and developing countries. Only a few of the literature (which focused mainly on central European foreign exchange markets) have produced limited results. For example, using a multivariate GARCH model, Lee (2010) studies volatility transmission across ten⁸ emerging foreign exchange markets. Here, the author provides evidence of regional and cross countries' volatility spillover. Bubák et al. (2011) examine the volatility transmission across three central European's emerging markets, in particular, among Czech, Hungarian and Polish currencies. Their main finding is a significant intra-regional volatility spillover across central European's foreign exchange markets.

⁷ The confidence channel represents the domestic agents' responses to the potential spillover coming from foreign shocks to the local economy (Eickmeier 2007).

⁸Five in Latin America (Chile, Brazil, Colombia, Peru, and Mexico) and five in Asia (South-Korea, Indonesia, Philippines, Thailand, and China)

In comparison to the above studies, this paper provides a thorough investigation of return and volatility spillover between developed and developing countries. In particular, the transmission through the foreign exchange market channel. We examine broad data samples from twenty-three⁹ developed and developing countries (which have received somewhat limited attention) before, during and after the recent financial crisis. The extended data sample from 2005 to 2016 emphatically help in a way, to unfold the effect of return and volatility spillovers across global foreign exchange markets, which currently dominate the focus of policymakers as well as financial managers.

3. Database and Methodology

3.1. Database

The underlying data employed in this study consists of daily spot exchange rates of currencies comprises a total of twenty-three developed and developing countries across the globe vis-á-vis the U.S. dollar. Taken from DataStream Thomson Reuters through the WM/Reuters channel the sample period starts in 31 May 2005 and ends in 01 June 2016. Since we investigate the spillovers effect between developed and developing countries, our study period facilitates the production of comprehensive and precise measures of return spillover and volatility spillover pre-and-post the recent financial crisis of 2007-09.

The series include currencies from ten developed countries, the British pound (GBP), euro (EUR), Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Japanese yen (JPY), Icelandic krona (ISK), Czech Republic koruna (CZK), Hong Kong dollar (HKD) Singapore dollar (SGD), and South Korean won (KRW), and currencies from eleven developing countries, including Russian ruble (RUB), Turkish lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentine peso (ARS), Malaysian ringgit (MYR), Thai baht (THB), Mexican peso (MXN), Saudi Arabian riyal (SAR), United Arab Emirates dirham (AED), South African rand (ZAR) and Nigerian naira (NGN). According to the Bank for International Settlement (BIS) report (2013), the underlying chosen currencies in this chapter include the most actively traded

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⁹ Currencies from nine developed countries, the British pound (GBP), euro (EUR), Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Japanese yen (JPY), Icelandic krona (ISK), Czech Republic koruna (CZK), Hong Kong dollar (HKD) Singapore dollar (SGD), and South Korean won (KRW) and currencies from eleven developing countries including the Russian roble (RUB), Turkish lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentine peso (ARS), Malaysian ringgit (MYR), Thai baht (THB), Mexican peso (MXN), Saudi Arabian riyal (SAR), United Arab Emirates dirham (AED), South African rand (ZAR) and Nigerian naira (NGN).

currencies across-financial markets globally. Moreover, it is also including currencies from oil rich countries such as Saudi Arabia.

3.2. Obtaining Daily Returns

To obtain the daily returns series, we calculate the daily change in log price of close data, when price data is not available for a given day due to a holiday or in the case of omitted value; we use the previous day value. As spot rates are non-stationary, we calculate the daily exchange rate returns as:

 $r_t = ln(y_t) - ln(y_{t-1})$, where y_t is the spot exchange rate at time t, with t = 1, 2....., T, and the natural logarithm ln. Table 1 provides a variety of descriptive statistics for returns.

3.3 Obtaining Daily Return Volatilities

A different approach could be employed to achieve the global foreign exchange market historical volatility, but in this study, we have followed the improved estimators of security price fluctuations of Garman and Klass (1980) and Alizadeh et al. (2002). The instinct of this methodology is that the underlying volatility estimators based on historical opening, closing, high and low prices and transaction volume. The underlying model assumption is that diffusion process governs security prices:

$$P(t) = \emptyset(B(t)) \tag{1}$$

Where P represents the security price, t is time, \emptyset is a monotonic time-independent¹⁰ transformation, and B(t) is a diffusion process with differential representation:

$$dB = \sigma \, dz \tag{2}$$

Where dz is the standard Gauss-Wiener process and σ is an unknown constant to be estimated. Implicitly the phenomenon is dealing with the transformed "price" series, and the geometrical price would mean logarithm of the original price, and volatility would mean "variance" of the original logarithmic prices. The original root of Garman and Klass methodology is the Brownian motion, where they added three different estimation methods. They based their methodology estimation on the notion of historical opening, closing, high and low prices and the transaction volume; through which they provided the following best analytic scale-invariant estimator:

$$\sigma_t = \sqrt{\frac{N}{n} \cdot \sum_{i=1}^{N} \frac{1}{2} \cdot (\log\left(\frac{H_i}{L_i}\right))^2 - (2 \cdot \log(2) - 1) \cdot \log\left(\frac{C_i}{O_i}\right)^2}$$
 (3)

Where σ_t is an unknown constant to be estimated, N is the number of trading days in the year and n is the chosen sample. H is today's high, L is today's low, O and C are

¹⁰ Monotonicity and time-independence both employed to assure that the same set of sample paths generates the sample maximum & minimum values of *B* and *P* Garman and Klass (1980).

today's opening and closing respectively. Explaining the coefficients of the above formulae is beyond the scope of this study for now. However, to obtain the foreign exchange market volatilities, we have used an intra-day high, low, opening and closing data. When price data is not available for a given day due to a holiday or in the case of omitted value, we use the previous day value. Table 2 shows descriptive statistics for global foreign exchange volatilities.

4. Methodology

To examine return and volatility spillovers across the broad cross-section of twenty-three global foreign exchange currencies, we have employed generalised vector autoregressive (VAR) methodology, focusing mainly on variance decompositions proposed by Diebold and Yilmaz (2009). The concept of variance decomposition is very rigorous and helpful as it allows the aggregation of valuable information across-markets into a single spillover index. In other words, how shocks in market A is due to exogenous shocks to other markets. Which best expressed by employing the phenomenon of variance decomposition concomitant with an N-variable VAR by adding the shares of the forecast error variance for each asset i coming from shocks to an asset j, for all $j \neq i$ tallying up across all $i = 1, \ldots, N$. Then considering the example of simple covariance stationary first-order two-variable VAR,

$$x_t = \Phi x_{t-1} + \varepsilon_t \tag{4}$$

Where $x_t = (x_{1t}, x_{2t})$ and Φ is a parameter matrix. In the following empirical work, x will be either a vector of foreign exchange returns or a vector of foreign exchange return volatilities. The moving average representation of the VAR is given by:

$$x_t = \Theta(L)\varepsilon_t \tag{5}$$

Where $\Theta(L) = (1 - \Phi L)^{-1}$ which for simplicity could be rewritten as:

$$x_t = A(L) u_t \tag{6}$$

Where, $A(L) = \Theta(L)Q^{-1}$, $u_t = Q_t \, \varepsilon_t$, $E(u_t \, u') = 1$, and Q^{-1} is the unique Cholesky factorisation of the covariance matrix of ε_t . Then considering the 1-step-ahead forecast, the precise approach would be the Wiener-Kolmogorov linear least-squares forecast as:

$$x_t + 1, t = \Phi x_t \tag{7}$$

With corresponding 1-step-ahead error vector:

$$e_t + 1, t = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix}$$
(8)

And comprises the following covariance matrix;

$$E(e_{t,+1,t} e'_{t+1,t}) = A_0 A'_0. (9)$$

To clarify, the variance of the 1-step-ahead error in forecasting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the 1-step-ahead error in forecasting x_{2t} is $a_{0,21}^2 + a_{0,22}^2$. Diebold and Yilmaz (2009) utilised the mechanism of variance decompositions to split the forecast error variances of each variable into parts attributable to a broader system shock. That facilitate answering the question of what fraction of the 1-step-ahead error variance in forecasting x_1 is due to shocks to x_1 ? And shocks to x_2 ?. And likewise, what portion of the 1-step-ahead error variance in forecasting x_2 is due to shocks to x_1 ? And shocks to x_2 ?

4.1. The spillover Index

Having understood the notion of variance decompositions described above, the spillover index of Diebold and Yilmaz (2009) then proposed representing the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j , for $i, j = 1, 2, i \neq j$. These two-variables construct the spillover index with two possible spillovers outcomes. First, x_{1t} which represents shocks that affect the forecast error variance of x_{2t} with the contribution ($a_{0,21}^2$). Second, x_{2t} similarly represents shocks that affect the forecast error variance of x_{1t} with a contribution ($a_{0,12}^2$) totalling the spillover to $a_{0,12}^2 + a_{0,21}^2$ which best expressed relative to the total forecast error variation as a ratio percentage projecting the spillover index as:

$$s = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A_{i_0})} \times 100 \tag{10}$$

The spillover index can be sufficiently generalised to wider dynamic environments particularly for the general case of a p^{th} -order N-variable VAR, using H-step-ahead forecast as:

$$s = \frac{\sum_{h=0}^{H-1} \sum_{i,j=1}^{N} a_{h,ij}^2}{\sum_{h=0}^{H-1} trace(A_h A_{h})} \times 100$$
(11)

To examine the data, the spillover index described above allows the aggregation degree of cross-market spillovers across the large data, which consists of 2872 sample into a single spillover measure. We use second-order 23 variable with 10-step-ahead forecasts.

4.2. Net Spillovers

To generate the net volatility spillovers, we follow (Diebold and Yilmaz 2012) by first calculating the directional spillovers. It can be done through normalising the elements of the generalised variance decomposition matrix. This way, we can measure the directional volatility spillovers received by (developing) countries from the developed countries or vice versa as follow:

$$S_{i.}^{\dot{g}} = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{\dot{g}}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{\dot{g}}(H)} \cdot 100 = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{\dot{g}}(H)}{N} \cdot 100.$$
(12)

Thus, from the above equation, the net volatility spillovers can be obtained from market i to all other markets j as follow:

$$S_i^{\dot{g}}(H) = S_i^{\dot{g}} - S_i^{\dot{g}}(H). \tag{13}$$

4.3. Net pairwise spillovers

Given the net volatility spillover described in equation (12), which provides the net volatility of each market contribution to others, then it is relatively easy to examine the net pairwise volatility as follow:

$$S_{ij}^{\dot{g}}(H) = \left(\frac{\widetilde{\theta}_{ji}^{\dot{g}}(H)}{\sum_{i,k=1}^{N} \widetilde{\theta}_{ik}^{\dot{g}}(H)} - \frac{\widetilde{\theta}_{ij}^{\dot{g}}(H)}{\sum_{j,k=1}^{N} \widetilde{\theta}_{jk}^{\dot{g}}(H)}\right).100 \tag{14}$$

$$= \left(\frac{\widetilde{\theta}_{ji}^{\dot{g}}(H) - \widetilde{\theta}_{ij}^{\dot{g}}(H)}{N}\right).100\tag{15}$$

Similarly, the net pairwise volatility spillover between market i and j represented by the difference between the gross volatility shocks communicated from market i to market j included those communicated from j to i.

4.4. ARCH Model

A basic autoregressive conditional heteroscedasticity (ARCH) model construct from two equations (a mean equation and a variance equation). The mean equation, which defines the behaviour of the time series data mean. So, the mean equation is the linear regression function, which contains constant and other explanatory variables. in the following equation, the mean function only contains an intercept:

$$y_t = \beta + e_t \tag{16}$$

Considering the eq.15, the time series is expected vary about its mean (β) randomly. In this case, the error of the regression is distributed normally and heteroskedastic too. The variance of the current error period depends on the information, which revealed in the proceeding period (Poon 2005). However, the variance equation defines the error variance behaviour where the variance e_t is given the symbol h_t as follow:

$$h_t = a + a_1 e_{t-1}^2 (17)$$

It is clear from eq.3.17 that h_t depends on the squared error in the proceeding time period (Bollerslev et al., 1994). Also, in this equation, the parameters have to be positive to ensure the variance h_t , is positive. In addition, the large multiplier (LM)

test can also be used to examine the presence of ARCH effects in the data, (i.e., whether α >0). However, to carry out this test, we estimate the mean equation, then saved and squared the estimated residuals, \hat{e}_t^2 . Then, for the first order ARCH model, we regressed \hat{e}_t^2 on the lagged residuals \hat{e}_{t-1}^2 and the following constant:

$$\hat{e}_t^2 = y_0 + y_1 \hat{e}_{t-1}^2 + v_t \tag{18}$$

Where, v_t represents the random term; and the null and alternative hypothesis are:

$$H_0: y_1 = 0$$

$$H_1: y_1 \neq 0$$

Table 7 shows the result of the large multiplier (LM) test which confirms the presence of ARCH in the data. So, the forecasted error variance is an in-sample prediction model essentially based on estimated variance function as follow:

$$\hat{h}_{t+1} = \hat{a}_0 + \left(r_t - \hat{\beta}_0\right)^2 \tag{19}$$

Figure 5 demonstrates the forecast error variance $((r_t - \hat{\beta}_0)^2)$ in a form of htarch, which reflects the years of our sample (2005 – 2016).

5. Empirical Results

5.1. Descriptive Statistics

Table 1 and 2 provide descriptive statistics of return and volatility spillovers, respectively. The underlying data consists of twenty-three¹¹ global currencies vis-á-vis the U.S. dollar and the sample size is 2871. Returns are calculated as a daily change in log price of close data (as described in the data section) and return volatilities as signified in equation (3.3) above. Currencies under research have been selected based on the most actively traded globally for both developed and developing countries.

¹¹ Currencies from ten developed countries, the British pound (GBP), euro (EUR), Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Japanese yen (JPY), Icelandic krona (ISK), Czech Republic koruna (CZK), Singapore dollar (SGD), Hong Kong dollar (HKD) and South Korean won (KRW) and currencies from eleven developing countries including the Russian ruble (RUB), Turkish lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentine peso (ARS), Malaysian ringgit (MYR), Thai baht (THB), Mexican peso (MXN), Saudi Arabian riyal (SAR), United Arab Emirates dirham (AED), South African rand (ZAR) and Nigerian naira (NGN).

The augmented dicky-fuller (ADF) test results (Table 1 and 2) for each currency is statistically significant, which means currencies under investigation are stationery. For the return's series (Table 1), fourteen¹²currencies recorded little negative means denoting slight appreciation (during the sample period) against the U.S. dollar. Whereas seven currencies recorded small depreciation including the Swiss franc (CHF), Singaporean dollar (SGD), Thai baht (THB), Hong Kong dollar (HKD), Saudi Arabian riyal (SAR), United Arab dirham (AED) and the South African rand (ZAR). Kurtosis coefficients are significantly high for developing countries in both returns and volatility spillovers. These are exciting facts indicate that the data distribution is leptokurtic¹³ which means the risk for the currencies of developing countries is coming from outlier events setting the ground for extreme remarks to arise. Moreover, the root means square-deviation ¹⁴ of volatility spillover series (Table 2) shows significant dispersion for eight developing countries.¹⁵ For more elaboration on the data, see Table (1 & 2) below.

¹² The euro, British pound (GBP), Australian dollar (AUD), Islandic krona (ISK), Czech Republic koruna (CZK), Turkey lira (TRY), Indian rupee (INR), Indonesian rupiah (IDR), Argentinian pesos (ARS), Malaysian ringgit (MYR), Mexican peso (MXN), South Korean won (KRW), Japanese yen (JPY) and the Nigerian naira (NGN).

¹³ Leptokurtic distribution said to have positive statistical value with higher peaks around the mean compared to normal distribution which in most circumstances leads to thick tails on both sides.

¹⁴ The root mean square-deviation is the other statistical term for the standard deviation.

¹⁵ Countries are India, Indonesia, Argentina, Malaysia, Thailand, Mexico, South Africa and Nigeria.

Table 1: Descriptive Statistics, Global Foreign Exchange Market Returns, 2005 -2016.

Mean	Country	United Kingdom	European Union	Australia	Canada	Japan
Standard Error 0.005				0.000	0.000	
Kurtosis 3,230 2,023 11,717 2,861 4,121 Skewness 0,408 -0,048 0,830 -0,036 -0,127 Minimum -0,029 -0,036 -0,067 0,033 -0,044 Maximum 0,039 0,029 0,095 0,158 0,039 ADF -51,4786** -53,4031** -55,7591** -54,8177** -58,9361 Country Switzerland Iceland Hong Kong Czech Republic Singapore Mean -0,000 0,000 -0,000 0,000 -0,000 Standard Error 0,007 0,010 0,000 0,008 0,003 Startosis 80.611 56,384 265,198 3,729 4,424 5kewness -2,676 0,238 -9,076 0,222 0,057 Minimum -0,157 -0,134 -0,032 -0,050 -0,022 ADF -53,7565** -55,5139** -44,7012** -54,0658** -54,7277** Country South Korea Russia Turkey	Standard Error				0.006	
Skewness 0.408 -0.048 0.830 -0.036 -0.127 Minimum -0.029 -0.036 -0.067 0.033 -0.044 Maximum 0.039 0.029 0.095 0.158 0.039 ADF -51.4786** -53.4031** -55.7591** -54.8177** -58.9361 Country Switzerland Iceland Hong Kong Czech Republic Singapore Mean -0.000 0.000 -0.000 0.000 -0.000 Standard Error 0.007 0.010 0.000 0.008 0.003 Kurtosis 80.611 56.384 265.198 3.729 4.424 Skewness -2.676 0.238 -9.076 0.222 0.057 Minimum -0.157 -0.134 -0.032 -0.053 0.022 Maximum 0.095 0.147 0.030 0.053 0.026 ADF -53.7565** -55.5139** -44.7012** -54.0658** -54.7277** Country <t< td=""><td></td><td></td><td></td><td></td><td>2.861</td><td></td></t<>					2.861	
Minimum -0.029 -0.036 -0.067 0.033 -0.044 Maximum 0.039 0.029 0.095 0.158 0.039 ADF -51.4786** -53.4031** -55.7591** -54.8177** -58.9361 Country Switzerland Iceland Hong Kong Czech Republic Singapore Mean -0.000 0.000 -0.000 0.000 -0.000 Standard Error 0.007 0.010 0.000 0.008 0.003 Kurtosis 80.611 56.384 265.198 3.729 4.424 Skewness -2.676 0.238 -9.076 0.222 0.057 Minimum -0.157 -0.134 -0.032 -0.050 -0.022 ADF -53.7565** -55.5139** -44.7012** -54.0658** -54.7277** Country South Korea Russia Turkey India Indonesia Mean 0.000 0.000 0.000 0.000 0.004 0.851	Skewness		-0.048	0.830	-0.036	-0.127
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Minimum -0.157 -0.134 -0.032 -0.050 -0.022 Maximum 0.095 0.147 0.030 0.053 0.026 ADF -53.7565** -55.5139** -44.7012** -54.0658** -54.7277** Country South Korea Russia Turkey India Indonesia Mean 0.000 0.000 0.000 0.000 0.004 0.851 Kurtosis 32.781 45.221 7.001 5.945 2729.823 5kewness 0.408 0.736 0.788 1.172 51.701 Minimum -0.103 -0.141 -0.053 -0.035 -0.098 Maximum 0.107 0.143 0.070 0.037 97.952 ADF -50.3963** -50.9994** -53.9350** -52.8286** -54.2572** Country Argentine Malaysia Thailand Mexico Saudi Arabia Mean 0.000 0.000 -0.000 0.000 0.000 0.000 Stewness 36.964 -0.369 <td>Kurtosis</td> <td>80.611</td> <td>56.384</td> <td>265.198</td> <td>3.729</td> <td>4.424</td>	Kurtosis	80.611	56.384	265.198	3.729	4.424
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Kurtosis 1657.464 5.182 149.717 13.351 42.832 Skewness 36.964 -0.369 1.659 0.962 0.568 Minimum -0.031 -0.035 -0.104 -0.061 -0.133 Maximum 0.355 0.029 0.115 0.081 0.153 ADF -36.8414** -53.5359** -53.5815** -23.8200** -53.5792** Country United Arab Emirates South Africa Nigeria Mean -0.000 0.000 0.025 Standard error 0.008 0.011 1.385 Kurtosis 77.821 25.199 2870.718 Skewness 0.769 1.691 53.572 Minimum -0.108 -0.065 -0.986 Maximum 0.122 0.175 74.250						
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Standard error 0.008 0.011 1.385 Kurtosis 77.821 25.199 2870.718 Skewness 0.769 1.691 53.572 Minimum -0.108 -0.065 -0.986 Maximum 0.122 0.175 74.250	Country	United Arab Emirates	South Africa	Nigeria		
Standard error 0.008 0.011 1.385 Kurtosis 77.821 25.199 2870.718 Skewness 0.769 1.691 53.572 Minimum -0.108 -0.065 -0.986 Maximum 0.122 0.175 74.250	Mean	-0.000	0.000	0.025		
Kurtosis 77.821 25.199 2870.718 Skewness 0.769 1.691 53.572 Minimum -0.108 -0.065 -0.986 Maximum 0.122 0.175 74.250						
Skewness 0.769 1.691 53.572 Minimum -0.108 -0.065 -0.986 Maximum 0.122 0.175 74.250						
Minimum -0.108 -0.065 -0.986 Maximum 0.122 0.175 74.250						
Maximum 0.122 0.175 74.250						
					*	

Notes: Returns are in real terms and measured by calculating the daily change in the log price of close data and the sample size is 2871. * P < 0.1; ** P < 0.05; *** P < 0.01.

Table 2: Descriptive Statistics, Global Foreign Exchange Market Volatility, 2005 – 2016.

Country U	Inited Kingdom	European Union	Australia	Canada	Switzerland
Mean	0.000	0.000	0.002	0.000	0.000
Standard error		0.002	0.072	0.000	0.009
Kurtosis	111.561	2866.973	1433.442	107.130	2802.957
Skewness	8.004	53.520	37.873	7.968	52.685
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	0.002	0.150	2.765	0.002	0.506
ADF	-31.2667**	-53.5757**	-30.9404**	-32.0489**	-53.5742**
Country	Japan	Iceland	Czech Republic	Hong Kong	Singapore
Mean	0.000	0.000	0.000	0.000	0.000
Standard error	r 0.000	0.001	0.000	0.000	0.000
Kurtosis	259.795	1429.986	65.781	760.508	709.547
Skewness	12.947	35.395	6.512	25.702	20.668
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	0.003	0.088	0.003	0.000	0.001
ADF	-42.3771**	25.7536**	-30.9438**	-15.8937**	-28.6243**
	12.0771	20.7000	50.7 100	10.0707	
Country	South Korea	Russia	Turkey	India	Indonesia
Mean	0.001	0.003	0.430	0.003	0.191
Standard error		0.155	23.055	0.128	2.665
Kurtosis	2871.851	2871.755	2871.999	1214.471	226.509
Skewness	53.588	53.587	53.591	34.377	14.893
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	4.751	8.310	1235.575	4.7415	42.769
ADF	-53.5699**	-53.5818**	-53.5817**	-53.6088**	-19.8196**
Country	Argentine	Malaysia	Thailand	Mexico	Saudi Arabia
Mean	0.000	-0.000	0.001	0.000	0.000
Standard error	0.000	0.004	0.088	0.000	0.000
Kurtosis	38.627	2843.605	2871.925	658.920	2785.065
Skewness	5.767	53.194	53.589	22.598	52.431
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	0.002	0.246	0.726	0.014	0.029
ADF	-36.8414**	-53.5359**	-53.5815**	-23.8200**	-53.5792*
Country U	United Arab Emirate	es South Africa	Nigeria		
Mean	0.000	0.000	0.025		
Standard error		0.021	0.541		
Kurtosis	2854.287	2868.012	750.063		
Skewness	53.347	53.535	25.985		
Minimum	0.000	0.000	0.000		
Maximum	0.003	1.161	18.821		
ADF	-53.5681**	-28.1001**	-37.4842**		
			01012		

Notes: Volatilities are for daily spot closing returns. We employ high-frequency intra-day data (high, low, opening and closing) to obtain the returns volatilities using formulae (3.3) described above. The sample size is 2871, consult text for more elaboration. * P < 0.1; ** P < 0.05; *** P < 0.01.

5.2. Return and Volatility Spillovers: Static Analysis (Spillover Tables)

The spillover index methodology we apply in this paper comprises two steps. First, we provide full static-sample analysis. Second, we successively proceed to interpret the dynamic rolling-sample version. By employing the spillover index, we extract return and volatility spillovers throughout the entire sample (2005 – 2016). Thus, we present the spillover indexes for both "returns and volatilities" in Table 3 and 4, respectively. The variables (i,j) placed under each table represent the contribution projected to the variance of the 10-week-ahead¹⁶ real foreign exchange (returns Table 1 and volatility Table 2) forecast error of country i coming from innovations to the foreign exchange (returns Table 1 and volatility Table 2) of country j.

In both tables, the lower corner of the first column from the right sums the "contributions from others" and similarly from the left sums the "contribution to others." The spillover tables designed to describe the input and output decomposition of the spillover index. Both products "input and output" help to successfully scrutinise the effect of return and volatility spillovers of global foreign exchange markets across developed and developing countries. With regard to return spillover (Table 3), touching on developed countries" "contribution to others", we observe that the GBP and the EUR are responsible for the most significant shares of the error variance in forecasting 10 week-ahead, totalling 102 percent and 100 per cent respectively. Also, some developing countries receive significant "return contribution" coming from the developed countries such as Thailand (100%) and Mexico (75%).

Moreover, due to the single European market, return spillover amongst developed countries is sizeable and positive. This means there are tremendous cross-market interconnectedness and financial interdependence amid developed countries.

However, considering the global foreign exchange volatility spillover, Table 4; it is clear that developed countries contribute significantly to their "own" total volatility spillover. This result is in line with the argument that the currency crisis tends to be regional (Glick and Rose 1998; Yarovaya et al. 2016). The results also show that intraregional volatility spillover transmission tends to be significantly higher than the inter-regional volatility spillover. Our finding is also in line with Melvin and Melvin, (2003); Cai et al. (2008) and Barunik et al. (2016) that significant volatility spillover transmitted amid currencies within a particular market.

Also, from table 4, we find that the pound sterling, euro and the Australian dollar are the main contributors of volatility spillover to others. Again, the result is in line with the findings presented by Antonakakis (2012); and Barunik et al. (2016) who found the GBP and the EUR to be the dominant net transmitters and receivers of volatility spillover during the period (2000 – 2013).

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¹⁶ Based on weekly vector auto-regressions of order 2, the results were generated and identified by a Cholesky factorisation.

Table 3
Spillover Table. Global Foreign Exchange (FX) Market Return, 31/05/2005 – 01/06/2016

From

		UK	EU	AUS	CAN	CHE	JPN	ISL	CZE	HKG	SGP	KOR	RUS	TUR	IND	IDN	ARG	MYS	THA	MEX	SAU	ARE	ZAF	NGA	From Others
	UK	99.0	0.0	0.0	0.4	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	1
	EU	0.0	99.	9 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
	AUS	0.0	0.0	99.3	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	1
	CAN	0.7	0.0	0.0	69.1	0.0	11.6	10.3	4.9	0.4	0.5	0.5	0.0	0.0	0.0	0.0	0.4	0.0	0.3	1.2	0.0	0.2	0.0	0.0	31
	CHE	0.0	0.	0.0	0.0	100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
	JPN	0.4	0.0	0.0	11.4	0.0	75.8	0.9	6.0	0.5	0.5	0.9	0.0	0.0	0.0	0.0	0.2	0.0	0.3	3.1	0.0	0.0	0.0	0.0	24
	ISL	0.1	0.0	0.0	0.3	0.0	3.8	88.2	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.2	0.0	0.5	6.3	0.0	0.0	0.0	0.0	12
	CZE	0.3	0.0	0.0	22.1	0.1	11.3	1.1	61.	5 0.3	1.7	0.1	0.0	0.0	0.0	0.0	0.3	0.0	0.5	0.5	0.0	0.0	0.0	0.0	38
	HKG	0.1	0.0	0.0	0.8	0.0	0.5	0.1	0.2	97.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.0	0.0	0.0	0.0	2
	SGP	0.3	0.0	0.0	5.8	0.0	3.8	0.4	7.8	0.2	80.9	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.4	0.0	0.0	0.0	0.0	19
То	KOR	0.0	0.0	0.0	0.1	0.0	0.4	0.2	0.1	22.7	0.0	76.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.1	0.0	0.0	0.0	0.0	24
	RUS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.6	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
	TUR	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	99.7	7 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
	IND	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0
	IDN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	99.7	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0
	ARG	0.2	0.0	0.0	1.6	0.0	5.4	0.5	2.7	0.3	0.2	0.1	0.0	0.0	0.0	0.0	85.1	0.0	1.4	8.0	0.0	0.0	1.6	0.0	15
	MYS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.9	0.0	0.0	0.0	0.0	0.0	0.0	0
	THA	0.0	0.0	0.0	0.1	0.0	0.4	0.2	0.1	22.7	0.0	76.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.1	0.0	0.0	0.0	0.0	100
	MEX	0.1	0.0	0.0	2.5	0.0	5.9	63.8	1.8	0.1	0.3	0.2	0.0	0.0	0.0	0.0	0.2	0.0	0.3	24.7	0.0	0.0	0.0	0.0	75
	SAU	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.3	0.0	0.0	0.0	1
	ARE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	99.8	3 0.0	0.0	0
	ZAF	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.4	0.0	0.5	0.0	0.0	0.0	98.0	0.0	2
	NGA	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.0	0.0	99.3	1
Contribution	to others	3	0	0	45	0	43	78	24	47	3	78	0	0	0	0	3	0	5	13	0	0	2	0	347
Contribution	including ov	vn 102	100	99	114	100	119	166	86	145	84	154	100	100	100	100	89	100	5	38	99	100	100	99	15.1%

Note: The fundamental variance decomposition is based on weekly (VAR) of order 2 identified using Cholesky factorisation. The value of (i, j) variables is the estimated contribution to the variance of the 10-day-ahead real foreign exchange (FX) return forecast error of country i coming innovations to real FX returns of country j.

Table 4

<u>Spillover Table: Global Foreign Exchange (FX) Market Volatility, 31/05/2005 – 01/06/2016</u>

From

		UK	EU	AUS	CAN	JPN	CHE	ISL I	HKG	CZE	SGP	KOR	RUS	TUR	IND	IDN	ARG	MYS	THA	MEX	SAU	ARE	ZAF	NGA	From Others
	UK	97.4	0.0	0.2	0.4	0.0	0.1	0.2	0.0	0.6	0.1	0.0	0.2	0.3	0.0	0.0	0.0	0.1	0.0	0.2	0.0	0.1	0.0	0.1	3
	EU	39.4	59.0	0.3	0.0	0.0	0.2	0.1	0.1	0.2	0.0	0.1	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	41
	AUS	24.8	6.2	62.5	1.5	0.0	0.3	0.7	0.0	0.2	0.2	0.1	0.1	1.4	0.1	0.0	0.0	0.1	0.0	1.4	0.1	0.1	0.2	0.0	37
	CAN	24.6	5.4	15.0	53.2	2 0.0	0.1	0.1	0.0	0.4	0.0	0.0	0.1	0.3	0.1	0.0	0.0	0.2	0.0	0.1	0.1	0.0	0.0	0.0	47
	JPN	0.1	0.1	0.1	0.1	98.1	0.0	0.4	0.0	0.1	0.2	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.2	0.0	0.0	2
	CHE	17.8	26.8	0.4	0.6	0.0	53.0	0.0	0.3	0.3	0.1	0.1	0.0	0.1	0.1	0.0	0.0	0.2	0.0	0.0	0.1	0.0	0.0	0.0	47
	ISL	14.4	10.7	1.2	0.3	0.1	0.4	69.4	1 0.4	0.1	0.4	0.3	0.0	0.1	0.0	0.0	0.1	0.1	0.1	1.9	0.0	0.0	0.1	0.0	31
	HKG	0.9	1.0	1.5	0.1	0.1	0.0	0.3	94.5	0.1	0.0	0.2	0.1	0.1	0.0	0.0	0.0	0.2	0.2	0.1	0.0	0.0	0.1	0.3	5
	CZE	33.7	38.8	0.8	0.4	0.0	0.1	0.1	0.0	25.3	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.2	0.1	0.0	0.1	0.0	75
	SGP	26.9	14.2	10.2	1.3	0.1	0.4	0.2	1.9	0.5	43.2	L 0.1	0.1	0.1	0.1	0.1	0.0	0.2	0.0	0.3	0.3	0.0	0.1	0.0	57
То	KOR	8.1	1.7	9.2	1.3	0.1	0.1	1.0	0.2	0.5	7.1	64.7	0.0	2.2	0.4	0.1	0.1	0.4	0.0	1.7	0.1	0.0	1.0	0.1	35
	RUS	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.1	98.1	0.0	0.1	0.1	0.	0.1	0.0	0.4	0.0	0.0	0.0	0.0	2
	TUR	13.2	4.3	10.2	3.5	0.1	1.2	0.6	0.0	1.8	1.1	0.4	0.1	61.9	0.0	0.0	0.0	0.0	0.0	0.9	0.1	0.0	0.5	0.0	38
	IND	6.8	1.6	4.8	0.9	0.3	0.1	0.3	0.2	0.1	2.9	1.7	0.2	2.0	76.1	0.2	0.0	0.3	0.0	1.1	0.1	0.0	0.3	0.0	24
	IDN	0.0	0.1	0.0	0.1	0.3	0.1	0.0	0.3	0.0	0.1	0.0	0.2	0.1	0.0	98.2	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	2
	ARG	0.1	0.0	0.4	0.1	0.1	0.0	0.0	0.0	0.0	0.2	0.1	0.1	0.0	0.0	0.2	98.3	0.1	0.0	0.1	0.0	0.0	0.0	0.0	2
	MYS	7.2	3.8	5.3	2.1	0.1	0.2	0.1	8.0	0.2	13.0	2.1	0.1	1.2	2.5	0.2	0.1	59.6	0.0	1.2	0.1	0.0	0.2	0.0	40
	THA	1.8	1.3	1.0	0.1	0.1	0.2	0.1	0.3	0.1	3.3	0.2	0.0	0.4	8.0	0.1	0.0	0.6	89.4	0.0	0.0	0.0	0.0	0.0	11
	MEX	14.4	2.7	8.7	8.4	0.0	1.1	0.2	0.2	2.0	3.6	0.4	0.1	4.7	0.3	0.3	0.0	0.2	0.0	52.7	0.1	0.0	0.0	0.0	47
	SAU	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.2	0.1	0.0	0.1	0.1	0.0	0.0	98.5	0.6	0.0	0.0	2
	ARE	0.0	0.0	0.1	0.1	0.3	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.6	98.6	0.0	0.0	1
	ZAF	18.5	5.1	10.7	4.	0.1	0.3	0.7	0.1	2.1	2.6	0.2	0.1	9.4	0.0	0.0	0.0	0.0	0.0	5.7	0.0	0.0	39.5	0.0	60
	NGA	0.1	0.2	0.0	0.0	0.1	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.1	0.0	0.0	0.0	98.8	1
Contribution	to others	253	124	80	26	2	5	5	5	9	35	6	2	23	5	2	1	3	1	16	2	1	3	1	610
Contribution	including ov	vn 351	183	143	79	100	58	75	99	35	78	71	100	85	81	100	99	63	90	68	100	100	42	99	26.5%

Note: The fundamental variance decomposition is based on daily (VAR) of order 2 identified using Cholesky factorisation. The value of (i, j) variables is the estimated contribution to the variance of the 10-day-ahead foreign exchange volatility forecast error of country i coming from innovation to the foreign exchange volatility of country j.

Following the discussion of the static version of volatility spillover transmission across global foreign exchange markets during the years of the sample, (2005 – 2016); a key finding is that developed countries contribute substantially to the total volatility transmitted (that is, contributions to others) and received (that is, contributions from others).

So far, we have shown evidence of return and volatility spillovers based on the static version analysis of the spillover indexes presented in table 3 (return) and table 4 (volatility). The indexes of 15.1% (for return) and 26.5% (volatility) represent the extracted cross-country spillover for the full sample (January 2005 –July 2016). This means virtually 26.5% of the forecast error variance comes from the spillover. Aside from scrutinising the broader static effect of return and volatility spillover across the global foreign exchange markets (between developed and developing countries), we now turn to provide a different fashion of the dynamic movement of return and volatility spillover effect.

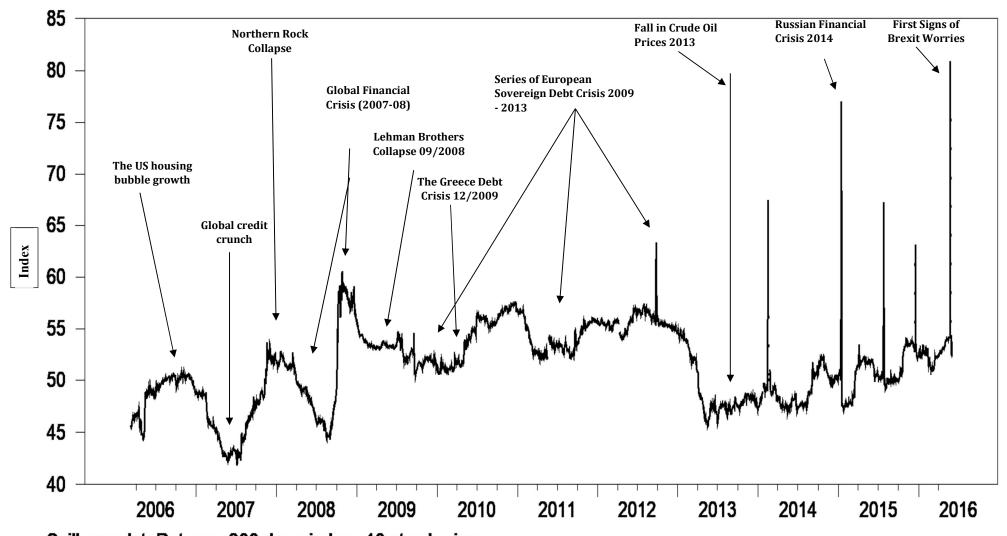
5.3. Return and Volatility Spillovers: Dynamic Analysis (Spillover Plots)

To address the extent of the spillover effect between developed and developing countries we use 200-day rolling samples, which is about six months. The 200-day rolling sample used to demonstrate the spillover variations over time between developed and developing countries since the data we use spans over 2005-2016. The dynamic movement of return and volatility spillovers is designed to capture the effect of the potential recurring movement of spillover by using returns and volatility indexes shown in Table 3 and 4. The indexes are the sums of all variance decompositions represented in the form of "contribution to others." Employing the indexes, we estimate the model using 200-day rolling samples to scrutinise the evolution of global foreign exchange markets during the years of the sample (2005 – 2016). Hence, we capture the magnitude and disparities of the spillover for return and volatility, which we present graphically in the form of spillover plots. The era of the 2000s, which began with a recession, mainly in developed countries across the European Union and the U.S. undisputedly, documented painful economic events in our history. In particular, the 2007/08 global financial turmoil. Thus, figure 1 for (return's spillover) captured some of the critical events, whereas figure 2, (volatility spillover) appears to be most eventful. Interestingly, the 200-day rolling samples epitomised in figure 1 and 2 highlights some of the significant economic events that occurred during the years of the sample (2005 – 2016). As the estimation window moves towards the year 2016, we have captured the following critical economic events;

1. The U.S housing bubble worries, according to Liebowitz (2008) foreclosure rates increased by 43 per cent during the 2^{nd} and the 4^{th} quarter of the year 2006.

- 2. The increasing of foreclosures and mortgage default rates reached about 55 per cent for (prime), and 80 per cent (subprime) hugely devalued mortgage-back-securities at the end of 2007, causing a severe credit crunch.
- 3. During the same year, the British bank Northern Rock collapsed.
- 4. Followed by Lehman Brothers, the biggest U.S. investment bank then, filed for bankruptcy on September 15, 2008.
- 5. Following the above events, among others, comes the worst financial turmoil (2007-2009) since the great depression of (1929 1939), and the Greece debt crisis, December 2009.
- 6. The series of European sovereign debt crisis (2009 2013),
- 7. The fall in Crude oil prices in 2014.
- 8. Russia financial crisis (2014 2017) according to the Centre for Eastern Studies (OSW), the leading causes of the Russian crisis are the tensions between Russia and the west which led to sanction war, and the dramatic fall in oil prices.
- 9. First signs of Brexit worries on June 23, 2016, whereby the British pound plunged to its lowest level since 1985.

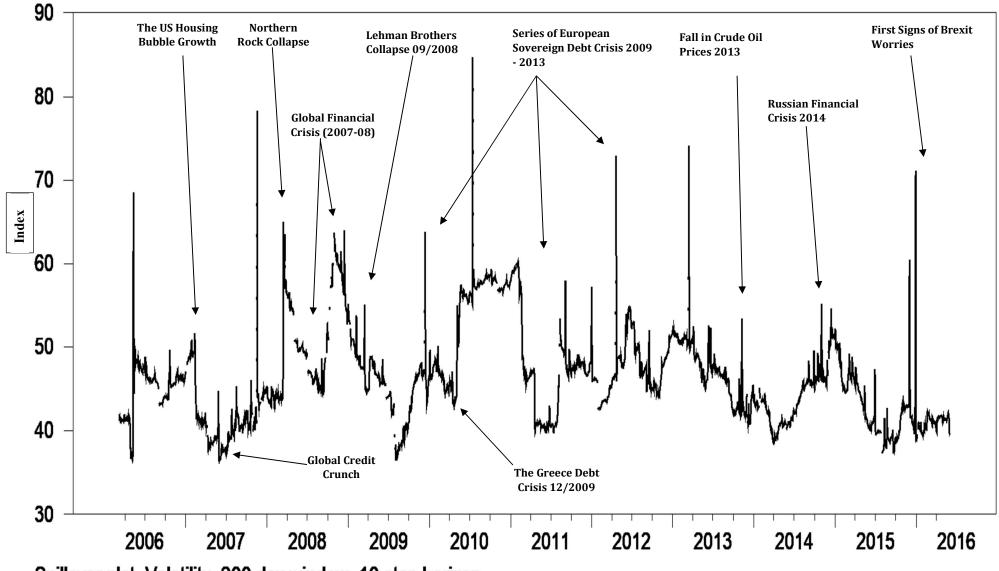
Figure 1.



Spillover plot. Returns. 200 day window. 10 step horizon

Ending Date of Window

Figure 2.



Spillover plot. Volatility. 200 day window. 10 step horizon

Ending Date of Window

The graphical illustrations above (Fig1 and Fig2) highlight important economic events during the years of the sample (2005 – 2016). The analysis orchestrated here, visually signalise the effect of spillover across intra-foreign exchange markets. The magnitude and extent of the spillover effect of both returns (figure 1) and volatility (figure 2) significantly marked by the crisis episodes of (2007 – 09) financial turmoil. In particular, the series of European sovereign debt crisis (2009 – 2014) and China stock market crash (2015), among others. This means, interestingly, besides volatility spillover, the contribution of return spillover is unexpectedly significant enough to show some commonality with volatility spillover in terms of responding to economic events. Further, we also observe bursts in total return and volatility spillovers which materialised twice in figure 1 and four times in figure 2, respectively. The total return's spillover began to decrease slightly after its strong response to the (2007 – 09) financial turmoil as well as the European sovereign debt crisis in 2009 until China stock market crash in (2015), whereby it shows a dramatic increase.

On the contrary, volatility spillover fluctuated with explicit outbursts virtually with every single economic event highlighted during the years of the full sample (2005 – 2016). Put it differently, the volatility spillover plot (figure 2), depicted the phenomenon of the globally systemically important financial institutions from a series of historical defaults involved too big to fail nature. To check the robustness of the result regarding rolling window width, forecast horizon, and VAR ordering, we perform spillover plots (figure 3) using an 84-day rolling window width. We also used two different variance decomposition forecast horizons; 70-day forecast horizon in figure 3 (a) and 14-day in figure 3 (b). The results are robust even when employing maximum and minimum volatility spillover across a diversity of alternative VAR ordering using 200-day rolling windows, see (figure 3 and 4).

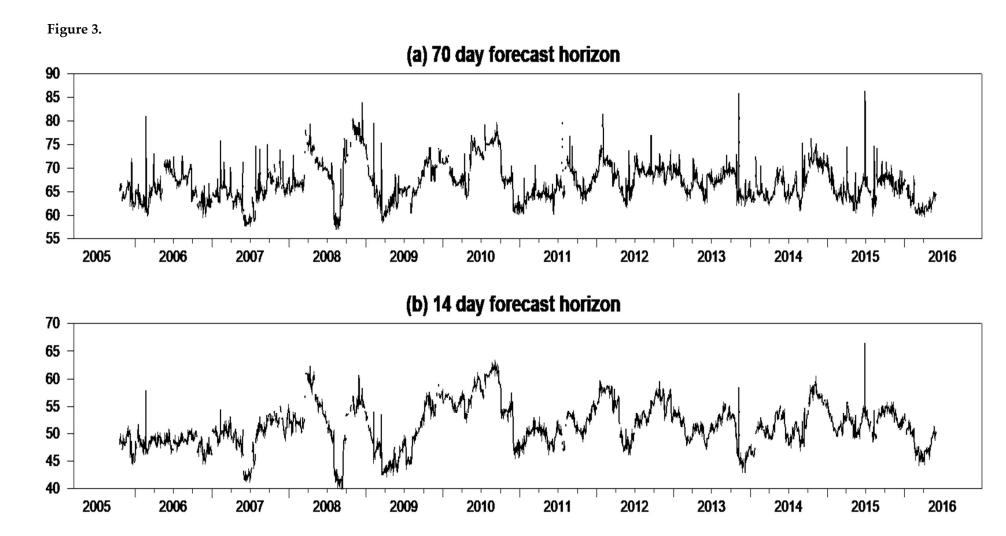


Figure 3 Spillover plot, Global FX Market Volatility 100 day Rolling Window

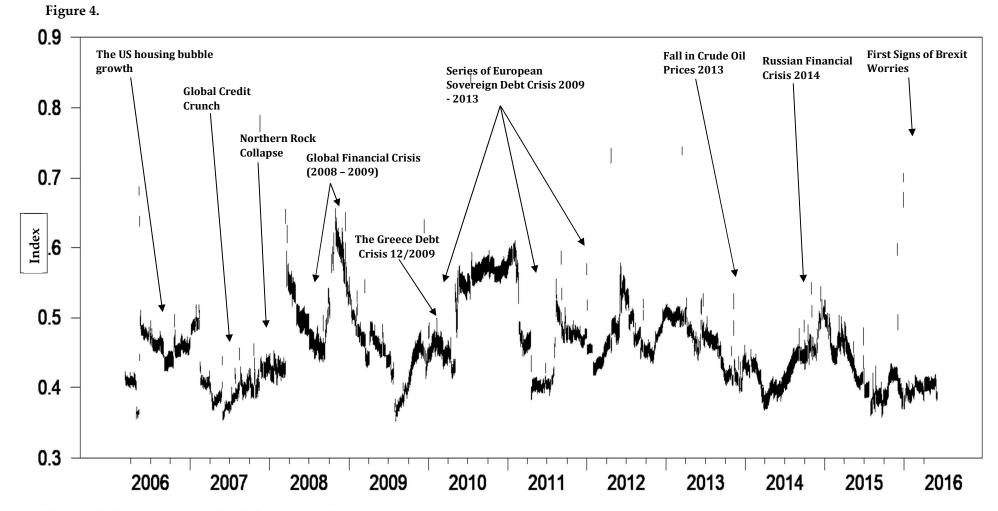


Figure 4. Maximum and minimum spillovers Randomly Chosen Orderings

Ending Date of Window

5.4. Robustness Analysis

Based on the extent of the above results, the maximum and minimum spillover figure 4, shows the variability of the volatility spillovers' magnitude in global foreign exchange markets, which appears to be relatively higher than return spillover. Notwithstanding, we find the behaviour of return spillover in the global currency markets (figure 1) substantially responding to major economic events during the years of the full sample (2005 – 2016). In contrast with the global stock market, Diebold and Yilmaz (2009) found the behaviour of return spillover insignificant and do not bear much resemblance with the behaviour of volatility spillover.

Since we find "contribution to others" mainly dominated by developed countries, in particular, the British pound (GBP), euro (EUR), and the Australian dollar (AUD), that make developing countries act as net receivers to return and volatility spillovers. Further, according to the Bank for International Settlements' (BIS) report (2013), the USD, EUR, GBP, AUD, CAD, JPY and the CHF are the most traded globally, account for almost 90 per cent of the global foreign exchange turnover. This means, a substantial amount of return and volatility spillovers transmitted across world during the years of the full sample (2005 – 2016) are coming from developed countries. The findings are robust even when employing maximum and minimum volatility spillover across a diversity of alternative VAR ordering using 200-day rolling windows.

Interestingly, the results highlight the significance of the global foreign exchange markets' spillover channels during crisis periods in several dimensions. One is the cyclical bursts in spillover occurs as a consequence of the significant economic events. These include, the credit crunch of July 2007, Lehman Brothers collapsed in September 2008, the financial turmoil which created havoc during 2007 – 09, the European sovereign debt crisis 2009 – 14 and the fall in Crude oil prices in 2013.

Two, it highlights the potential magnitudes of the spillover effect, particularly from the default of systemically important financial institutions across the global financial system, which spread jitters from the outset of the U.S. subprime mortgage crisis. Three, the size of the shocks which led to bursts in spillover (see, figs. 1, 2, 3 and 4) suggest strong cross-market interconnectedness which reflects the definition of "contagion" presented by Forbes and Rigobon (2002). To Four, the results also provide significant insights, particularly to the financial regulators from the perspectives of understanding the effect of spillover from the default of systemically important financial institutions. Finally, they also introduce for investors the issue of crossmarket linkages and economic interdependence during crises periods whereby volatility spillover increases substantially.

¹⁷ Forbes and Rigobon (200) defined contagion as "a significant increase in cross-market linkages after a shock to one country or group of countries."

5.5.Time-varying volatility spillovers

In this section, we present the results of the time-varying volatility spillover among developed developing countries; using autoregressive heteroskedasticity (ARCH). Time varying volatility helps investigate sources of significant shifts in the volatility during the years of our sample (2005 – 2016). This is because the ARCH models designed to capture persistence in time varying volatility based on squared returns (Poon, 2005). This is due to the nature of the Arch model where 'autoregressive' means high volatility tends to persist, 'conditional' refers to time-varying or specific point on time, and 'heteroskedasticity' refers to non-constant volatility (Poon, 2005). Before applying the Arch (1) model, we first generate the squared residuals using regression, which contains only an intercept. 18 Table 5 shows the regression result of the squared residuals, which called ehat2. This is because the squared residuals ensure that the conditional variance is positive and consequently, the leverage effects cannot be captured by the Arch model (Engle, 2001b).

Table 5: Regression (ehat2 L.ehat2)

Variable	Adjusted <i>t</i> *	p-value
Ehat2	8.12	0.000
No obs: 2.871;	R – squared: 0.022; Adj R-squared: 0.022;	MSE: 1.3e-07

Second, we test the data for the presence of Arch effects using the Box-Pierce large multiplier (LM), which provides the most appropriate results (Alexander, 2001). Table 6 displays the result of the large multiplier's (LM) test for the presence of Arch effects in the data.

Table 6: LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	64.443	1	0.0000
H0: no ARCH effects	vs. H1: ARCH(p) disturbance		

The LM results show the null and alternative hypotheses, the statistic and its distribution and the p-value, which indicates the presence of Arch (p) model disturbance in the data. Thus, we estimate the Arch (1) model and generate the forecast error variance, which is essentially an in-sample prediction model based on the estimated variance function, (see equation 3.19 for more details). Table 7 shows the result of the conditional variance of the estimated Arch (1) model, which is saved as a variable called htarch. The conditional variance in the Arch model is allowed to change over time as a function of past error leaving the unconditional variance constant (Bollerslev, 1986). Then we proceed by plotting the forecast error variance

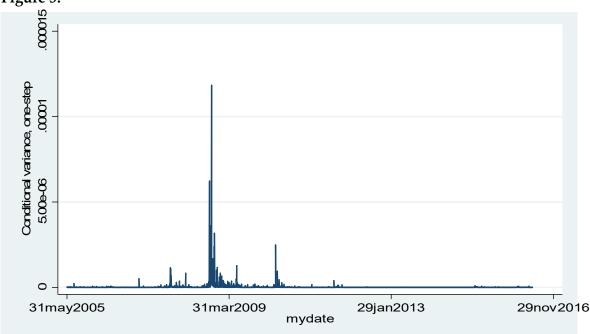
¹⁸ For more elaboration, see the methodology section (2.3.4. above).

(htarch) against the years of our sample (2005 – 2016). Figure 5 shows the result of Arch (1) model, which implies that the volatility spillovers from developed countries to the developing countries seem to be specifically strong in 2008.

Table 7: htarch ht_1 in 496/500

4	9	6	•		2	8	0	е	-	0	9	2	8	0	е	-	0	9
4	9	7		;	2	2	4	e	-	0	9	2	2	4	e	-	0	9
4	9	8			2	9	9	e	-	0	9	2	9	9	e	-	0	9
4	9	9		;	2	5	6	e	-	0	9	2	5	6	e	-	0	9
5	0	0			4	0	2	e	-	0	9	4	0	2	e	-	0	9





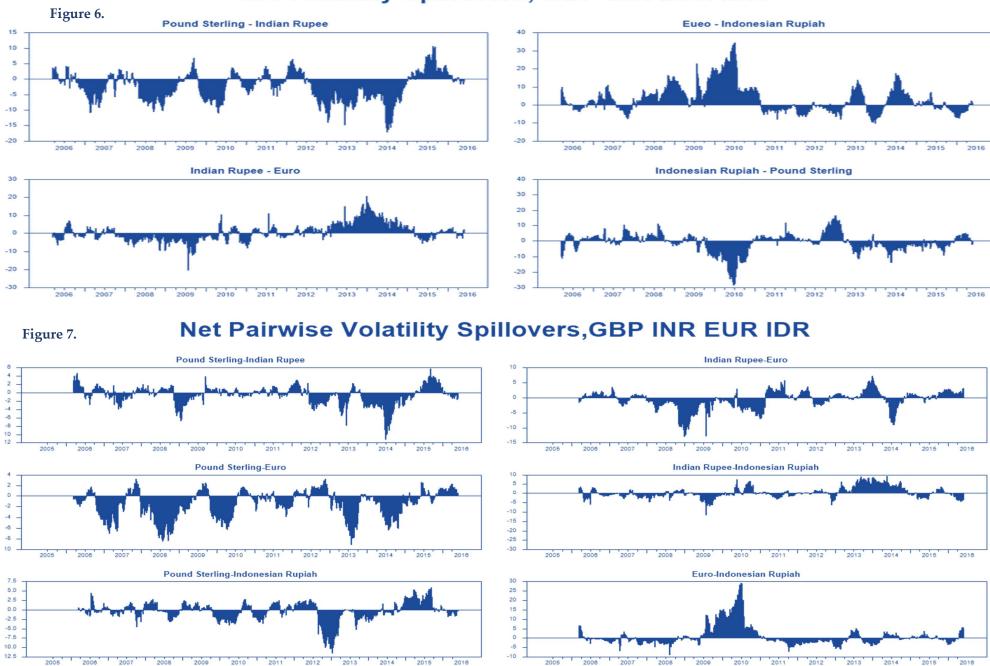
Thus, the result indicates that the foreign exchange market channel between developed and developing countries exhibit time-varying persistence in its conditional volatilities over crisis periods. This result is consistent with the spillover index findings of both static analysis (Table 4) and the dynamic analysis (Figures 2 & 4). It also shows that all the currencies in the sample from both (developed and developing) countries are characterised by clustering volatility. Our finding indicates that the global foreign exchange market experiences somewhat relatively sedate volatility spillovers from 2005 to 2007. Then, the foreign exchange market's volatility spillovers become much more volatile in 2008-2009. These results are consistent with the dynamic analysis of the spillover indices (Fig 2) which captured the 2008/09 financial crisis.

5.6. Net spillovers and net pairwise volatility spillovers

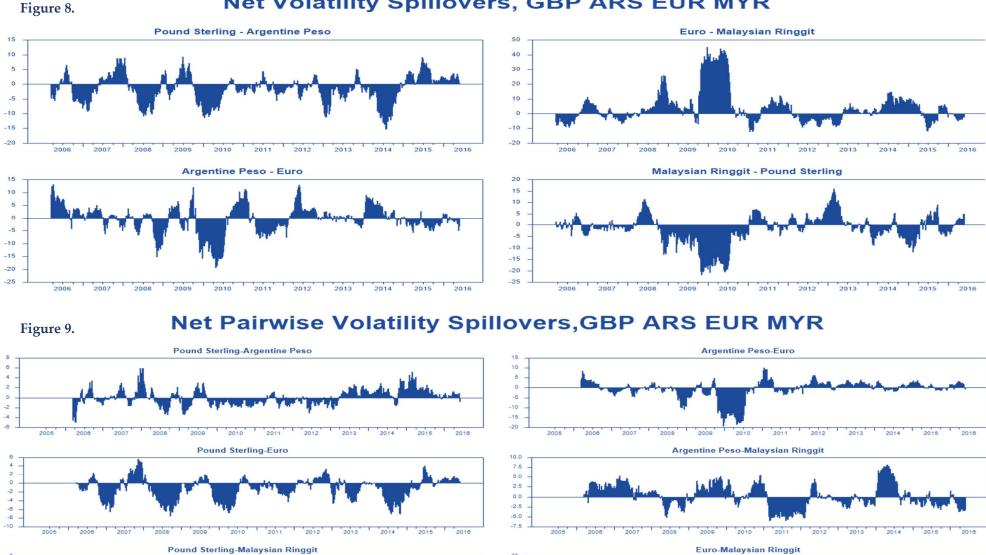
This section presents the results of the net spillover and the net pairwise spillover between developed and developing countries over the years of our sample (2005 – 2016). The key features of the net volatility spillover, it shows the difference between the gross volatility shocks that are transmitted to, and those received from all other markets (Diebold and Yilmaz, 2012). Thus, the net pairwise volatility spillover (Eq.14) between country i and j is the difference between the gross volatility shocks transmitted from country i to country j including the transmission from j to i (Diebold and Yilmaz, 2012). As shown in Eq. (12), the net volatility spillover offers important information about the amount of volatility in net terms, that each country contributes in other countries. Therefore, the main focus point of this section, is to calculate the net volatility and the net pairwise volatility spillovers between developed and developing countries. Due to the large number of countries (23) in our sample only 16 currencies selected, which we present in Figs. 6-9.

During the years of our sample (2005 -2016), there were two major events of net volatility spillovers through the global foreign exchange market, in particular during the 2008/09 financial crisis and the European sovereign debt crisis in 2009/13. However, before the recent financial crisis and the European sovereign debt crisis, the net volatility spillovers between developed and developing countries was relatively low. But things changed drastically after 2007 where the net volatility spillover from the EUR to the Malaysian ringgit Fig.8 jumped to 20% in the third quarters of 2008 and 40% in the third quarters of 2009. These results are consistent with the time-varying volatility results; which implies that the foreign exchange market experiences low volatility from 2005 to 2007. The pound sterling (GBP) and the euro (EUR) Figs. 6-9 both acts as giving and receiving of the net volatility transmissions, with almost similar magnitudes across the global foreign exchange market. This finding supports the static analysis of the spillover index (Table 4) that the pound sterling (GBP) and the euro (EUR) are the main contributors of volatility spillovers.

Net Volatility Spillovers, GBP INR EUR IDR



Net Volatility Spillovers, GBP ARS EUR MYR



2013 2014

The Indonesian rupiah (IDR) also receives significant amount of volatility spillovers from the euro (EUR) Fig. 7, especially during the recent financial crisis and the European sovereign debt crisis in 2009/13. On the other hand, the euro (EUR) receives a large amount of volatility spillover from the Malaysian ringgit (Fig. 9), which indicates that developed countries act as receivers and transmitters of volatility spillovers. The Argentine peso (ARS) contributes as well as receives significant amount of volatility from the Malaysian ringgit (MYR), Fig. 9.

The net volatility spillovers from the pound sterling (GBP) to the euro (EUR) Fig. 9 seems relatively low, while receiving significant amount of volatility spillovers from the euro (EUR). The fact that the pound sterling (GBP) contributes as well as receives large amount of volatility spillovers from the euro (EUR) shows the increased link between developed countries in the global foreign exchange market.

6. Conclusion

The critical question was whether the effects of return and volatility spillovers are bidirectional between developed and developing countries. Thus, in this study, we examined the impact of return and volatility spillovers on global foreign exchange markets across developed and developing countries. Quoted against the U.S. dollar, the data sample comprises twenty-three global currencies across developed and developing countries. Seven out of which are the most actively traded globally, including the British Pound (GBP), Euro (EUR), Australian Dollar (AUD), Swiss Franc (CHF), Icelandic Krona (ISK), Czech Republic Koruna (CZK), Hong Kong Dollar (HKD). We discussed the effect of return and volatility spillover between developed and developing countries using the generalised vector autoregressive (VAR) methodology. Thus, we provide results of the spillover index empirically in the form of static analysis 'the spillover tables' as well as a dynamic analysis in the form of 'spillover plots. We also discussed the time-varying volatility spillover among developed and developing countries; using autoregressive conditional heteroskedasticity (ARCH).

During the years of the sample investigation (2005 – 2016), several exciting economic events reveal the magnitude and extent of the volatility spillover's effect across global foreign exchange markets. In particular, from the perspective of the recent financial markets' interconnectedness. Nevertheless, the findings do not disclose evidence of bidirectional spillover between developed and developing countries. However, we find non-negligible evidence of unidirectional spillovers (table 4) from developed to developing countries. We

also found that developed countries act as receiver and transmitter of volatility, dominated by the British pound (GBP), Australian dollar (AUD), and the euro (EUR), whereas developing countries are a net receiver of volatility. Further, the empirical results conclusively show that the magnitude and extent of the return and volatility spillovers are significantly large within the European region (Eurozone and non-Eurozone currencies). In particular, during the crisis episodes, whereby the volatility spillovers replicate remarkable bursts. This phenomenon is in line with the findings presented by Glick and Rose (1998); and Yarovaya et al., (2015) that the currency crises tend to be regional.

From a policy point of view, this chapter documents significant practical implications. First, the extent of global foreign exchange markets' volatility channel highlights the significance of contagion and systemic risk, particularly from the globally systemically important financial institutions. Second, the substantial return spillovers between developed countries, especially within the European region (Eurozone and non-Eurozone currencies) further quantify the importance of cross-market linkages and the recent financial innovations. Third, it also opens avenues for a better understanding of the potential crisis of a highly interlinked nature mirrored in the historical economic events.

Finally, this chapter contributes to the scarce literature of intra-foreign exchange markets, from the perspective of developed and developing countries. Here, the empirical results show that the spillover channels between developed and developing countries are insignificant. However, this raises the question about how the recent financial turmoil (which affected both developed and developing countries) propagated across the global economies? To conclude, the results presented in this chapter, highlight the need for further research examining the magnitude and extent of the volatility spillover from the default of systemically important financial institutions. From the viewpoint of policymakers, the highlevel of financial interconnectedness within the European countries is of extreme concern.

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