Resul Aydemir
Corresponding author

Istanbul Technical University,
Department of Economics,
Turkey

✉ resulaydemir@itu.edu.tr

Bulent Guloglu

Istanbul Technical University,
Department of Economics,
Turkey

✉ guloglub@itu.edu.tr

Ercan Saridogan

Istanbul University,
Department of Econometrics,
Turkey

✉ ercan.saridogan@istanbul.edu.tr

Volatility Spillovers and Dynamic Correlations among Foreign Exchange Rates and Bond Markets of Emerging Economies

Summary: In this paper, we first examine how important historical shocks during and after the 2007-2008 global financial crisis affect the size and the persistence of volatilities among exchange rates and the ten-year bond rates of the Fragile Five countries (i.e., Brazil, India, Indonesia, South Africa and Turkey). We then investigate separately the dynamic interactions between exchange rates and the ten-year bond rates of the Fragile Five. We utilize a multivariate GARCH model (FIAPARCH-DCC model) and volatility impulse response functions to achieve these objectives. The results suggest that shocks' positive impacts on expected conditional variances of the variables are largely market-specific and different. Shocks have a more significant impact on bond markets than on foreign exchange markets. We also find that the dynamic conditional correlation series of bonds exhibit much lower correlations than those associated with exchange rate returns.

Key words: Volatility spillovers, Exchange rates, Interest rates, Dynamic correlations, Emerging markets.

JEL: C32, F31, G12, G15.

The 2007-2008 global financial crisis reached its peak when Lehman Brothers declared its bankruptcy on September 15, 2008 (the Lehman shock in the paper) which resonated throughout the world's financial markets including those of developing countries. To avoid the risk of a financial collapse, the U.S. Federal Reserve (the Fed) has taken steps to launch several quantitative easing programs. As a result, billions of US dollars poured into the equity and bond markets of emerging countries. Sizable capital inflows significantly increased asset prices in emerging markets. However, after mid-2013 this trend tended to be reverse mainly due to the tapering decision of the Fed. The Fed's first exit signal from the quantitative easing programs was given by Chairman Bernanke on May 22, 2013 during a Congress hearing (the Tapering 1 shock). Eventually, the Fed announced its tapering decision (the Tapering 2 shock) on December 18, 2013 which amounted to reducing asset purchases beginning in January 2014.

These historical shocks are well known to have had a huge impact on foreign exchange, money and credit markets, especially in emerging countries such as Brazil,

India, Indonesia, South Africa and Turkey, recently labelled the *Fragile Five*[1]. These countries were viewed to be most at risk when the tapering began due to their certain shared characteristics such as high inflation, high current account deficit and low growth during these turbulent times. Their currencies and assets prices fell substantially more than those of other emerging countries during this period (Prachi Mishra et al. 2014). In this paper, we have four goals. Specifically, we examine how the three historical shocks mentioned above affect not only the size but also the persistence of the volatilities first among the exchange rates, second among the ten-year bond rates of the *Fragile Five*, third we investigate separately the dynamic interactions between the exchange rates, and fourth between the ten-year bond rates of the *Fragile Five*. To that end, we estimate a FIAPARCH-DCC model and derive dynamic (time varying) conditional correlations and then we analyze the effects of these historical shocks on the volatilities of exchange rates and interest rates using the volatility impulse response functions (VIRFs) developed by Christian M. Hafner and Helmut Herwartz (2006).

The paper is organized as follows. After this introduction, Section 1 reviews the related literature. The model and data are presented in Section 2. Estimation results are discussed in Sections 3 and 4, before the concluding remarks in Section 5.

1. Literature Review

Due to increasing interdependency and contagion between countries under the highly globalized financial markets, understanding the interaction dynamics of the financial indicators has been very crucial for decision makers recently. In particular, through magnifying volatility, financial shocks have great effects on the financial variables and markets across the world economy. There is a large empirical literature on volatility transmission models across financial markets and financial indicators. However, to the best of our knowledge, the literature on volatility transmission between exchange rates and interest rates for the countries of the *Fragile Five*, except individual country studies, hardly exists. We first briefly review the literature of the methodologies for volatility transmission and then the literature on the empirical studies for volatility transmission across financial indicators by focusing on the forex and bond markets.

The multivariate GARCH (MV-GARCH) models have been widely used for modelling volatility transmission recently. These models allow one to analyze the interrelations between financial markets. In a multivariate framework they permit one to model not only the mean of the variables but also the variance of the variables in both the short- and the long-run. For example, Tim Bollerslev (1986) transforms the ARCH model of Robert F. Engle (1982) into the generalized autoregressive conditional heteroskedasticity (GARCH) model by allowing the conditional variance to be an ARMA process in ARCH models. Since then, the ARCH-family models have developed rapidly and have been used to characterize financial markets extensively (Bollerslev, Ray Y. Chou, and Kenneth F. Kroner 1992; Bollerslev 2009). Luc Bauwens, Sébastien Laurent, and Jeroen V. K. Rombouts (2006) distinguish three approaches for constructing multivariate GARCH models. The first approach provides direct generalizations of the univariate GARCH model of Bollerslev (1986) such as the VEC, BEKK and

---

[1] In their August 2013 report, Morgan Stanley analysts called these countries as the Fragile Five.

factor models, flexible MGARCH, Riskmetrics, Cholesky and full factor GARCH models. The second deals with linear combinations of univariate GARCH models such as (generalized) orthogonal models (GOGARCH) and latent factor models. The third involves nonlinear combinations of the univariate GARCH models such as the constant (CCC) and dynamic conditional correlation models (DCC); the general dynamic covariance model and copula-GARCH models.

Among various multivariate GARCH models in the literature, we use the FIAPARCH-DCC model to analyze volatility spillovers. Additionally, to trace out the effects of historical shocks we employ volatility impulse response functions (VIRF) for multivariate time series exhibiting conditional heteroscedasticity. Hafner and Herwartz (2006) introduce the volatility impulse response function (VIRF). They propose a method to calculate VIRF for the *vec* representation of a multivariate GARCH model, which nests the most popular multivariate GARCH specifications, and is used to investigate the complicated behaviour of financial time series.

Most of the earlier studies analyzing dynamic interactions and volatility spillovers between financial variables have been carried out using linear GARCH-DCC models with the Gaussian distribution assumption for innovations. However, many financial series are fat tailed and skewed so that the Gaussian distribution assumption could not be validated. In addition, linear models cannot take into account asymmetry and long memory properties of financial variables. The FIAPARCH-DCC model with *t* distributions, allowing for asymmetry and long memory, would be a more appropriate approach to examine some key financial variables.

Engle (2002) extends constant correlation (CCC) model of Bollerslev (1990) to the dynamic conditional correlation multivariate GARCH (DCC MV-GARCH) model, which allows for correlations to change over time and preserves the parsimony of univariate GARCH models of individual assets' volatility with a simple GARCH-like time-varying correlation. The number of parameters to be estimated using maximum likelihood is also *O(k),* which is a considerable improvement over both the VECH and the BEKK models and the number of parameters requiring simultaneous estimation is *O(1)* (Engle and Kevin Sheppard 2001).

Richard T. Baillie, Bollerslev, and Hans Ole Mikkelsen (1996) introduce Fractionally Integrated Generalized AutoRegressive Conditionally Heteroskedastic (FIGARCH) model. They state that "*the FIGARCH model implies a slow hyperbolic rate of decay for the lagged squared innovations in the conditional variance function, although the cumulative impulse response weights associated with the influence of a volatility shock on the optimal forecasts of the future conditional variance eventually tend to zero; a property the model shares with weakly stationary GARCH processes*".

The empirical literature that studies volatility transmission across financial markets at the country-specific, regional or global level focuses on volatility transmission across various financial assets including equities, bonds, currencies and commodities in the spot and future markets. The papers consider different economic crises, monetary policy shocks, news effects by employing different empirical methodologies briefly explained above. Table 1 presents some selected empirical studies related to volatility transmission. Studies mainly examine the volatility transmission between various financial and economic indicators.

Table 1 Empirical Literature on the Volatility Transmission for Financial Indicators

Author(s)	Year	Method	Period	Findings
John Wei-Shan Hu et al.	1997	Causality, GARCH	1992-1996 daily	Differentiated interrelationships among the stock markets.
Charles M. Jones, Owen Lamont, and Robin L. Lumsdaine	1998	ARCH-M	1979-1995 daily	Announcement-day volatility does not persist at all, consistent with the immediate incorporation of information into prices.
Edward S. Lim, John G. Gallo, and Peggy E. Swanson	1998	VECM	1988-1993 monthly	Bidirectional causality exists between stock market returns and bond market returns.
George A. Christodoulakis and Stephen E. Satchell	2002	Corr-GARCH	1985-1996 monthly	Fitting well the CorrARCH/CorGARCH to the data set from the G7 stock markets and stylized facts in the literature, such as time variation, persistence, volatility and correlation comovement.
Vasiliki D. Skintzi and Apostolos N. Refenes	2006	EGARCH, DCC	1991-2002 monthly	Significant volatility spillovers exist from both the aggregate Euro area bond market and the US bond market to individual European markets.
Kosta Josifidis, Jean-Pierre Allegret, and Emilija Beker Pucar	2009	VAR/VEC	1990-2009 monthly	The comparison of the Polish, Czech and Slovak economies with the Serbian case shows strong and persistent exchange rate pass-through, low interest rate pass-through, significant indirect and direct influence to the exchange rate as potential obstacles for successful inflation targeting in the Republic of Serbia.
Essahbi Essaadi, Jamel Jouini, and Wajih Khallouli	2009	DCC with structural breaks	1995-1999 monthly	Existence of shift contagion on stock markets' returns caused by the crisis in Thailand
Nikolaos Giannellis, Angelos Kanas, and Athanasios P. Papadopoulos	2010	EGARCH, causality in mean and variance	1970-2002 monthly	Significant reciprocal volatility spillovers between the stock market and economic activity within UK
Eric Olson, Andrew J. Vivian, and Mark E. Wohar	2014	BEKK, CCC, DCC, VIRF	1985-2013 daily	Low S&P 500 returns cause substantial increases in the volatility of the energy index; a weak response from S&P 500 volatility to energy price shocks.
Joscha Beckmann and Robert Czudaj	2014	GARCH-M, VAR	2000-2012 daily	The impact of the volatility of corn futures returns on the returns of cotton and wheat futures is statistically significant.
Mohamed El Hedi Arouri, Amine Lahiani, and Duc Khuong Nguyen	2015	VAR-GARCH	2004-2011 daily	Significant volatility transmission between the Chinese stock market and the world gold market.
Walid Mensi et al.	2016	DCC-FIAPARCH	1997-2013 daily	Evidence of asymmetry and long memory in the conditional volatility and significant dynamic correlations between the U.S. and the BRICS stock markets
Menelaos Karanasos, Stavroula Yfanti, and Michail Karoglou	2016	FIAPARCH-DCC	1988-2010 daily	Dynamic correlations across stock markets are highly persistent and during the crisis periods they tend to show an upward pattern. After financial crises the markets become more interdependent.
Zekeriya Yildirim	2016	SVAR	2006-2015 daily	(i) Global financial risk shocks have significant effects on government bond yields, equity prices, CDS spreads, and exchange rates in the Fragile Five. (ii) The effects differ considerably across the fragile countries and assets. (iii) These country differences are strongly correlated with macroeconomic fundamentals. (iv) Global financial risk shocks have a greater immediate effect on local currency government bond and CDS markets than on FX and stock markets.

Pedro Pires Ribeiro and José Dias Curto	2017	MGARCH	2006-2015 daily	Volatility spillovers are time-varying and very responsive to major economic events, increasing in periods of higher turbulence.
Dimitrios Dimitriou, Dimitris Kenourgios, and Theodore Simos	2017	ECM-A-DCC	2004-2015 daily	The Canadian Dollar and the British Pound were affected mainly by the US Dollar across the two crises due to strong financial and economic ties among the three economies. Evidence of varying vulnerability of currencies to both crises.
Mensi, Shawkat Hammoudeh, and Sang Hoon Kang	2017	DCC-FIAPARCH	1997-2013 daily	Significant time-varying correlations between the selected stock markets, suggesting that investors' risk appetite changes over time particularly after 2007-2009.
Karanasos et al.	2018	UEDCC-AGARCH	2007-2012 daily	Copper and gold futures returns exhibit time-varying persistence in their corresponding conditional volatilities over the crisis period; such persistence increases during periods of high volatility compared with low volatility.
Ahmet Sensoy et al.	2018	cDCC-FIAPARCH	2002-2014 daily	An almost perfect integration of the European Monetary Union (EMU) sovereign bond markets in the pre-crisis period. The integration structure is then severely damaged, reflected by an all time low group correlation in the EMU, following the collapse of Lehman Brothers and the realization of fiscal problems in Greece.
Evžen Kočenda and Michala Moravcová	2019	DCC-GARCH	1999M1-2018M5.	Significant differences in the extent of currency co-movements during various periods related to market distress. Low correlations reflect different patterns of behavior in the world forex market and in new EU currencies during crisis periods.

Source: Authors' compilation.

Using varying methodologies to analyse volatility spillovers, the authors investigate different samples of countries and periods. Therefore, the results vary across studies. One of the main findings is that significant volatility spillovers are largely market-specific and different. The authors also find significant time-varying correlations between financial assets and volatilities of these assets which usually substantially increase during crises including the recent global financial crisis. Earlier research using linear GARCH-DCC models suffers from asymmetry and long memory problems. However, recent papers take into account these issues and provide more robust findings. As the above review suggests, most papers in the literature focus on the linkage between stock markets among developed or emerging markets. Moreover, although studies using VIRF analysis and FIAPARCH-DCC models separately looking at different assets are available in the literature, none of them specifically focus on foreign exchange and bond markets in the *Fragile Five* countries. We contribute to the literature to fill this gap by examining the dynamic interactions between exchange rates and bond rates of the *Fragile Five* in the context of the global financial crisis and the taper tantrum.

2. Model and Data

We obtained daily data for the ten-year bond rates and foreign exchange rates of Turkey, Brazil, India, Indonesia and South Africa from Bloomberg. In the exchange rate analysis, the sample ranges from 02 January 2007 to 04 November 2016 with 2569 observations, whereas 1683 observations of the ten-year bond interest rates of these five countries from 27 January 2010 to 03 November 2016 are used in the ten-year bond market investigation. Note that the ten-year bond data for Turkey prior to January

2010 is not available. The continuously compounded return of a market at time t is calculated as follows:

$$R_{it} = log\ (P_{it}/P_{it-1}),\tag{1}$$

where P_{it} and P_{it-1} are the exchange rates of country i against the US-dollar at time t and t-1, respectively. The ten-year bond rates (i.e., yields) provided by Bloomberg are measured in local currency. The data for weekends and holidays are excluded from the sample. It is important to note that the levels of bond rates and the returns of exchange rates are stationary. But the levels of exchange rates are nonstationary. Throughout the paper, whenever we talk about exchange rates, we refer to their compounded returns unless otherwise stated. However, by the bond rates we simply mean their levels rather than their compounded returns.

Table 2 presents the summary statistics and the Augmented Dickey-Fuller (ADF) unit root test statistics for the daily returns of the exchange rates and the level of ten-year bond rates. The exchange rate returns and the bond rates demonstrate common characteristics observed in the financial time series. All the exchange rate returns except Brazil and Indonesia are positively skewed and highly leptokurtic. Those returns are not normally distributed as shown by Jarque-Bera statistics. Regarding bond rates, we see that the Brazil bond rate is positively skewed, whereas all the others exhibit negative skewness. All the bond rates are also highly leptokurtic. They are not normally distributed indicated by Jarque-Bera statistics as expected as all of them are significant at 1% level. Daily values of the exchange rates and bond rates in the sample are illustrated in Figures A1 and A2 in the Appendix, respectively. We observe tremendous increases in volatility after the Lehman and Tapering shocks. The ADF test statistics associated with exchange rate returns and levels of ten-year bond rates are all significant at 1% level indicating that they are stationary.

Table 2 Summary Statistics for Daily Exchange Rates Returns and Ten-Year Bond Rates

	Exchange rate returns					Ten-year bond rate (level)				
	Brazil	Indonesia	India	South Africa	Turkey	Brazil	Indonesia	India	South Africa	Turkey
Mean	0.0002	0.0003	0.0001	0.0003	0.0003	12.0936	7.4905	8.0541	8.1477	9.2363
Median	0.0000	0.0000	0.0000	0.0001	-0.0001	12.3640	7.7820	8.0450	8.2040	9.4100
Maximum	0.0846	0.1007	0.0989	0.0922	0.0652	16.8390	9.8840	9.2400	10.3810	11.3600
Minimum	-0.1194	-0.1581	-0.0772	-0.0694	-0.0568	9.1170	5.0470	6.6740	6.0320	6.1000
Std. dev.	0.0104	0.0098	0.0069	0.0108	0.0085	1.5613	1.1483	0.4743	0.6788	1.0865
Skewness	-0.1062	-0.6412	1.0821	0.3387	0.5871	0.4935	-0.4200	-0.1688	-0.4896	-0.7501
Kurtosis	16.266	41.972	32.331	8.121	10.335	3.8210	2.2812	2.8860	3.3991	3.4154
Jarque-Bera	18843	162753	92590	2856	5906	115.594	85.722	8.904	78.411	169.928
ADF stats	-37.50	-40.72	-37.33	-37.01	-36.69	-36.55	-28.48	-23.69	-31.81	-35.50
Observations	2569	2569	2569	2569	2569	1683	1683	1683	1683	1683

Notes: All Jarque-Bera test (test for normality) statistics are significant at 1% level. The Augmented Dickey-Fuller (ADF) is a unit root test for stationarity. All statistics are significant at 1% level.

Source: Authors' own calculations.

2.1 Volatility Impulse Responses

In this study the volatility impulse responses are obtained using the diagonal BEKK model developed by Engle and Kroner (1995). The main advantage of BEKK specification is that it provides positive variances and the number of parameters to be estimated is reduced. The BEKK (1, 1) model we consider is as follows[2]:

$$H_t = CC' + Au_{t-1}u'_{t-1}A' + GH_{t-1}G', \tag{2}$$

where matrix H is symmetric and contains conditional variances and covariances, C is a lower triangular matrix, and A and G are the parameter matrices. Matrix A captures how the conditional variance is correlated with past squared residuals, and hence measures the impact of shocks on volatility. Matrix G indicates the degree to which the conditional variances and covariances are linked to conditional variances and covariances of the previous period. Thus, it measures volatility spillovers. The residuals (u_t) are obtained from a VAR model and following Engle and Kroner (1995):

$$u_t = H_t^{\frac{1}{2}}\varepsilon_t, \tag{3}$$

where $E(\varepsilon_t) = 0, var(\varepsilon_t) = I_K$ and K is the number of variables.

In all cases, we accommodate the residuals to follow a student t distribution. This is justified since series have excess kurtosis and skewness as shown in Table 1.

The student t-distributed residuals also accommodate the volatility impulse responses advanced by Hafner and Herwartz (2006). In fact, the volatility impulse response function delineates the impact of an "independent" shock on volatility of the variables. The independence of shocks from each other permits shocks to be obtained from historical data to construct volatility impulse response functions. However, in a multivariate framework it is hard to assume that shocks are independent if they occur at the same time. Cholesky decomposition is widely used for the orthogonalization of residuals. As an alternative to the Cholesky decomposition method, Hafner and Herwartz (2006) use the Jordan decomposition to obtain independent shocks. Consequently, the impulse responses that are obtained turn out to be free from issues involving ordering of the variables. Moreover, to trace out the effects of a historical shock related to a specific event, we estimate the model for the whole sample rather than using a sub-period corresponding to that event.

Using the Jordan decomposition Hafner and Herwartz (2006) decompose H_t in order for identical and independent shocks to be obtained from Equation (1) as follows:

$$H_t^{\frac{1}{2}} = \Gamma_t \Lambda_t^{\frac{1}{2}} \Gamma'_t. \tag{4}$$

After the decomposition, the independent shocks can be given as:

$$\varepsilon_t = H_t^{-\frac{1}{2}} u_t. \tag{5}$$

The volatility impulse responses $V_t(\varepsilon_0)$ are defined as the difference between the expectation of volatility conditional on an initial shock and the history

---

[2] The BEKK results, which are available upon request, are not reported in order to save space.

$E(vech(H_t)|\varepsilon_0, \Omega_{-1})$ and conditional on history only $E(vech(H_t)|\Omega_{-1})$. Thus, a one-step ahead volatility impulse response is obtained as:

$$V_1(\varepsilon_0) = F\left\{vech\left(H_0^{\frac{1}{2}}\varepsilon_0\varepsilon_0'H_0^{\frac{1}{2}}\right) - vech(H_0)\right\} = FD_K^+\left(H_0^{\frac{1}{2}}\otimes H_0^{\frac{1}{2}}\right)D_K vech(\varepsilon_0\varepsilon_0' - I_K)$$
$$\text{for } t = 1,$$

(6)

where F is the coefficient matrix obtained from vech representation of Equation (1) and D_K^+ and D_K represent the Moore-Penrose inverse and duplication matrix, respectively. For $t \geq 2$, the volatility impulse responses are obtained as follows:

$$V_t(\varepsilon_0) = (F+G)^{t-1}FD_K^+\left(H_0^{\frac{1}{2}}\otimes H_0^{\frac{1}{2}}\right)D_K vech(\varepsilon_0\varepsilon_0' - I_K) = (F+G)V_{t-1}(\varepsilon_0)$$
$$\text{for } t \geq 2.$$

(7)

2.2 Dynamic Correlations

To analyze dynamic correlations between exchange rates and bond rates we employ a multivariate AR(1)-FIAPARCH-DCC model. The FIAPARCH specification allows for an asymmetric response of volatility to positive and negative shocks and also long memory volatility dependence. The FIAPARCH combines the FIGARCH specification of Baillie, Bollerslev, and Mikkelsen (1996) and the APARCH model of Zhuanxin Ding, Clive W. J. Granger, and Engle (1993). In this paper, we use the FIAPARCH (1, d, 1) specification as follows:

$$(1 - \beta L)h_t^{*\frac{\delta}{2}} = \omega + \left[(1-\beta L) \quad (1-\lambda L)(1-L)^d\right](|z_t| - \gamma z_t)^\delta,$$

(8)

where $\omega > 0$, $\delta > 0$, $\beta < 1$ and $\lambda < 1$.

The innovations which follow student-t distributions are derived from an AR(1) model. In Equation (8), γ stands for the leverage parameter and δ represents the power term and d $(0 \leq d \leq 1)$ is the long memory parameter, which captures persistence and long memory in volatility. It should be noted that for the conditional variances to be positive the sufficient condition (Christian Conrad and Berthold R. Haag 2006 and Conrad 2010) is that:

$$\beta - d \leq \lambda \leq \frac{(2-d)}{3} \text{ and d}\left(\lambda - \frac{1-d}{2}\right) \leq \beta(\lambda - \beta + d) \text{ and } \omega > 0.$$

(9)

Moreover, the FIAPARCH reduces to the APARCH when $d = 0$ and to GARCH when $\delta = 2$ and $\gamma = 0$.

After the FIAPARCH specification is fitted for all series in the first step, in the second step to estimate the DCC parameters the series are transformed using the estimated standard deviations obtained from the FIAPARCH models. We apply the DCC approach developed by Engle (2002) to obtain the time varying correlations. Following Engle (2002), suppose H_t^*, R_t and D_t denote the $n \times n$ conditional covariance matrix, the conditional correlation matrix, and a diagonal matrix with time-varying standard deviations on the diagonal, respectively. Then we can write H_t^* as follows:

$$H_t^* = D_t R_t D_t,$$

(10)

$$D_t = diag\left(\sqrt{h_{11,t}^*}, \ldots, \sqrt{h_{nn,t}^*}\right), \tag{11}$$

where the terms $h_{ii,t}^*$ are conditional variances obtained from AR(1)-FIAPARCH(1, d, 1) model.

$$R_t = diag(q_{1,t}^{-1/2}, \ldots q_{n,t}^{-1/2}) \; Q_t diag(q_{1,t}^{-1/2}, \ldots q_{n,t}^{-1/2}) \tag{12}$$

$$Q_t = (1 - \theta - \alpha)\bar{Q} + \theta \; (u_{t-1}^* \; u_{t-1}^{*'}) + \alpha \; Q_{t-1}, \tag{13}$$

where $Q_t = (q_{ij,t})$ is nxn symmetric positive definite matrix and $\bar{Q}$ is the unconditional correlation matrix of the standardized residuals u_{it}^* ($u_{it}^* = \frac{z_{i,t}}{\sqrt{h_{i,t}}}$). The parameters θ and α are positive and satisfy the condition that $\theta + \alpha < 1$. The innovations $z_{i,t}$ are assumed to be conditionally *t*-distributed and are obtained from an AR (1) specification to each series:

$$y_t = cons + \phi y_{t-1} + z_t \text{ with } |\phi| < 1. \tag{14}$$

The dynamic correlations can be obtained as follows:

$$\rho_{ij,t} = \frac{(1-\theta-\alpha)\bar{q}_{ij} + \theta \; u_{i,t-1}^* \; u_{j,t-1}^* + \alpha \; q_{ij,t-1}}{\sqrt{\left[(1-\theta-\alpha)\bar{q}_{ij} + \theta \; u_{i,t-1}^{*2} + \alpha \; q_{ij,t-1}\right]} \sqrt{\left[(1-\theta-\alpha)\bar{q}_{ij} + \theta \; u_{j,t-1}^{*2} + \alpha \; q_{ij,t-1}\right]}}. \tag{15}$$

$$i \neq j$$

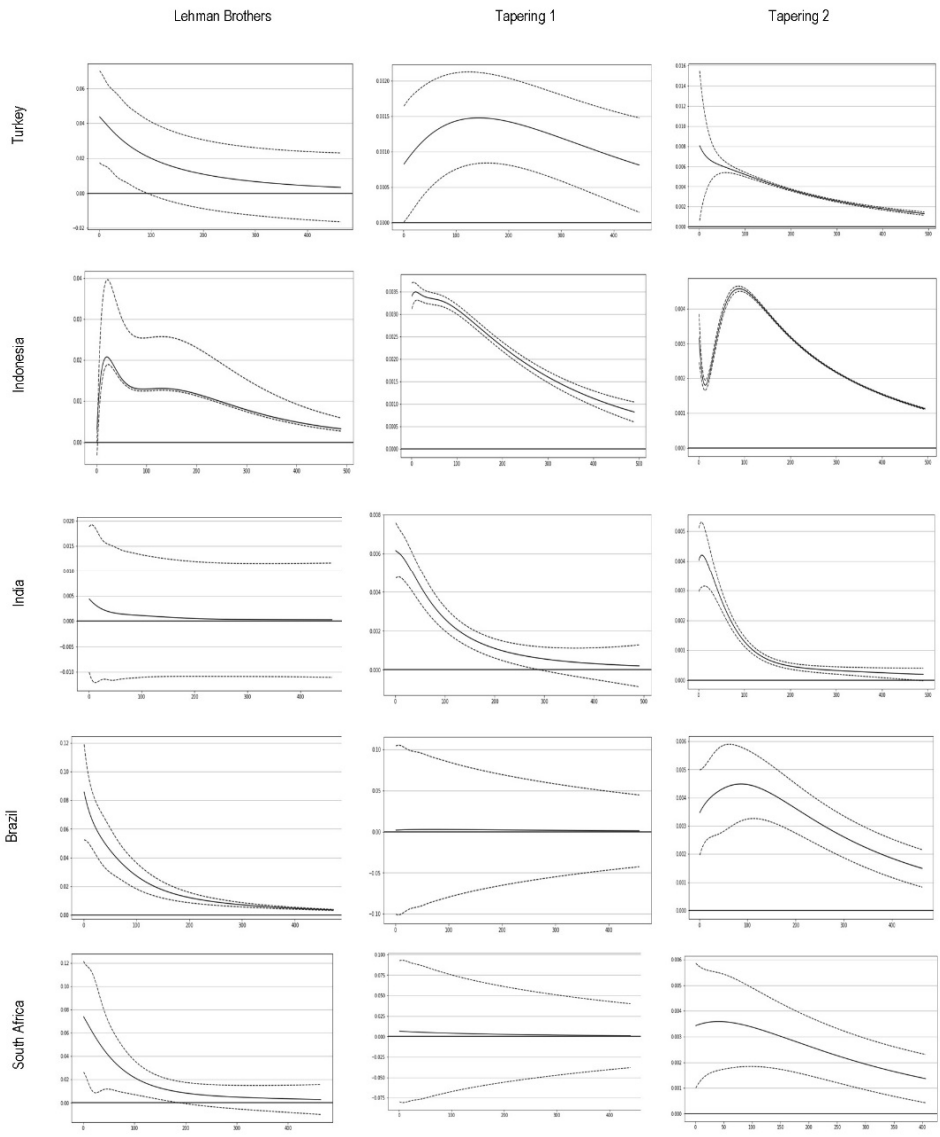## 3. Estimation Results - Volatility Impulse Responses

3.1 Volatility Impact from Past Shocks: Foreign Exchange Markets

In this section, we illustrate the volatility impulse response function analysis for the foreign exchange markets. We consider three historical shocks: Lehman Bankruptcy, Tapering 1 (i.e., Bernanke's first exit signal from the quantitative easing programs) and Tapering 2 (the Fed's tapering decision), which are within the sample period.

3.1.1 The Lehman Bankruptcy

Figure 1 shows the time pattern of the impulse response of volatilities after each historical event. Regarding the Lehman shock, it demonstrates that there are significant volatility increases stemming from this shock on four conditional variances (except India) after the Lehman bankruptcy. This suggests that the Lehman bankruptcy event has a significant but different impact on each currency in the sample. We find the largest positive effect for the post-Lehman era for the returns of Brazil's currency. Its one-step ahead expected conditional variance is increased by around 8.5%. The post-bankruptcy positive impact in expected conditional variance of exchange rate returns of South Africa, Turkey, Indonesia and India are about 7%, 4%, 2% and 0.4%, respectively for the one-step ahead expected conditional variance. The impact is not

statistically significant for India however. Hence, in terms of impact (the maximum value of the VIRF, which is to say the peak value), we have the following ranking for the countries in the sample (from highest to lowest): Brazil > South Africa > Turkey > Indonesia > India.

Source: Authors' own calculations.

Figure 1 Volatility Impulse Responses Functions for Exchange Rate Returns with 99% Confidence Intervals

Except for Indonesia, the impact is instantaneous for all other countries. The largest response of conditional variance happens after 25 days for Indonesia. The results reported above indicate that all four countries' exchange rates except India exhibit a responsiveness to shocks and that their magnitudes are higher than that of India's exchange rate. These findings may reflect the fact that India is more insulated and Brazil is more fragile to shocks relative to other emerging markets. The trade characteristics of Brazil indicate that its export revenues are highly sensitive to commodity prices as commodity products account for most of its exports. Besides, commodity prices are expressed in US dollars and the two (i.e., commodity prices and the US dollar) have been negatively correlated between 2003 and mid-2016. Therefore, it is unsurprising to see that volatility in Brazil's currency strongly depends on the US economy and movements in the USD (Riadh Aloui, Mohamed Safouane Ben Aïssa, and Nguyen 2011). On the other hand, unlike Brazil, Indian exports rely mostly on manufactured products and we observe a relatively low degree of openness in trade for India. This factor in turn insulates the Indian rupee against global financial shocks such as the Lehman bankruptcy (Dimitriou, Kenourgios, and Simos 2013). Furthermore, the effects of the shock reveal that the durations of the impacts are relatively long. In other words, the impact of the shock seems to be highly persistent for all countries.

Overall, the findings associated with the Lehman shock suggest that the sensitivity of foreign exchange markets from the impact of shocks are largely market-specific and different, although the foreign exchange markets concurrently soak up shocks. While Brazil seems to be more volatile and responsive than other markets regarding the volatility impulse response analysis associated with the Lehman collapse, India is the least responsive to the shock both in terms of size and persistency.

3.1.2 The Tapering Events

Tapering talks have inundated the global financial markets especially after Chairman Bernanke's speech during a U.S. Congress hearing on May 22, 2013 when he gave the first exit signal from the Fed's quantitative easing programs. Eventually, the Fed announced its tapering decision on December 18, 2013 signaling that it would reduce its purchases of bonds and other financial assets from banks beginning in January 2014. Since tapering basically indicates the end of easy money in financial markets, emerging economies especially those of the *Fragile Five* have been adversely affected by this decision. In this study, in addition to the Lehman shock, we investigate the impact of these two events, the exit signal by Bernanke on May 22, 2013 (Tapering 1) and the Fed's announcement of tapering decision on December 18, 2013 (Tapering 2) on foreign exchange rates volatilities as well.

Figure 1 shows that there are statistically significant volatility increases resulting from impact of the Tapering 1 shock on conditional variances of exchange rate returns of Turkey, Indonesia and India after Bernanke's exit signal. However, the size of the impacts is much lower than that of the Lehman shock. The positive impact for the post-Tapering 1 on expected conditional variance of exchange rate returns of India, Indonesia and Turkey are about 0.6%, 0.35% and 0.1 % respectively for the one-step ahead expected conditional variance. Unlike the Lehman shock, while India seems to be more volatile and more responsive than other markets regarding the volatility

impulse response analysis associated with Tapering 1, Brazil is the least sensitive to the shock both in terms of size and persistency. Indeed, the impact of the shock is not statistically significant for Brazil and South Africa. To sum up, both the size and persistency of the impact of the shock on exchange markets are much less than the Lehman shock.

Tapering 2 seems to have a more significant impact than Tapering 1 on the volatilities of exchange rate returns. Specifically, the positive impact for the post-Tapering 2 on the expected conditional variance of exchange rate return of Turkey, Indonesia, Brazil, India and South Africa are about 0.6%, 0.45%, 0.45%, 0.4% and 0.35%, respectively, for the one-step ahead expected conditional variance. Hence, in terms of impact (peak), we have the following ranking for the countries (from highest to lowest): Turkey > Brazil > Indonesia > India > South Africa. We also find that the impact tends to gradually disappear within significantly longer period than Tapering 1, but in much shorter period than the Lehman impact does.

Overall, our findings indicate that in terms of both size and persistency the Lehman shock has a more significant impact on the exchange rate volatilities in the *Fragile Five* than both tapering events. During the taper tantrum, capital flowed out of emerging economies which caused their currencies to depreciate. To avoid sudden or large depreciation, authorities intervene in foreign exchange markets. Guillermo A. Calvo and Carmen M. Reinhart (2002) document that some emerging market economies with floating exchange rates are actually unwilling to allow their currencies fluctuate in response to shocks, which they call the "fear of floating". Indeed, the *Fragile Five* countries which were susceptible to the fear of floating took measures such as currency intervention and policy rates increases to maintain stability in their currency markets during the taper tantrum. Our findings related to the tapering shocks are consistent with the earlier literature and these measures (Yildirim 2016).
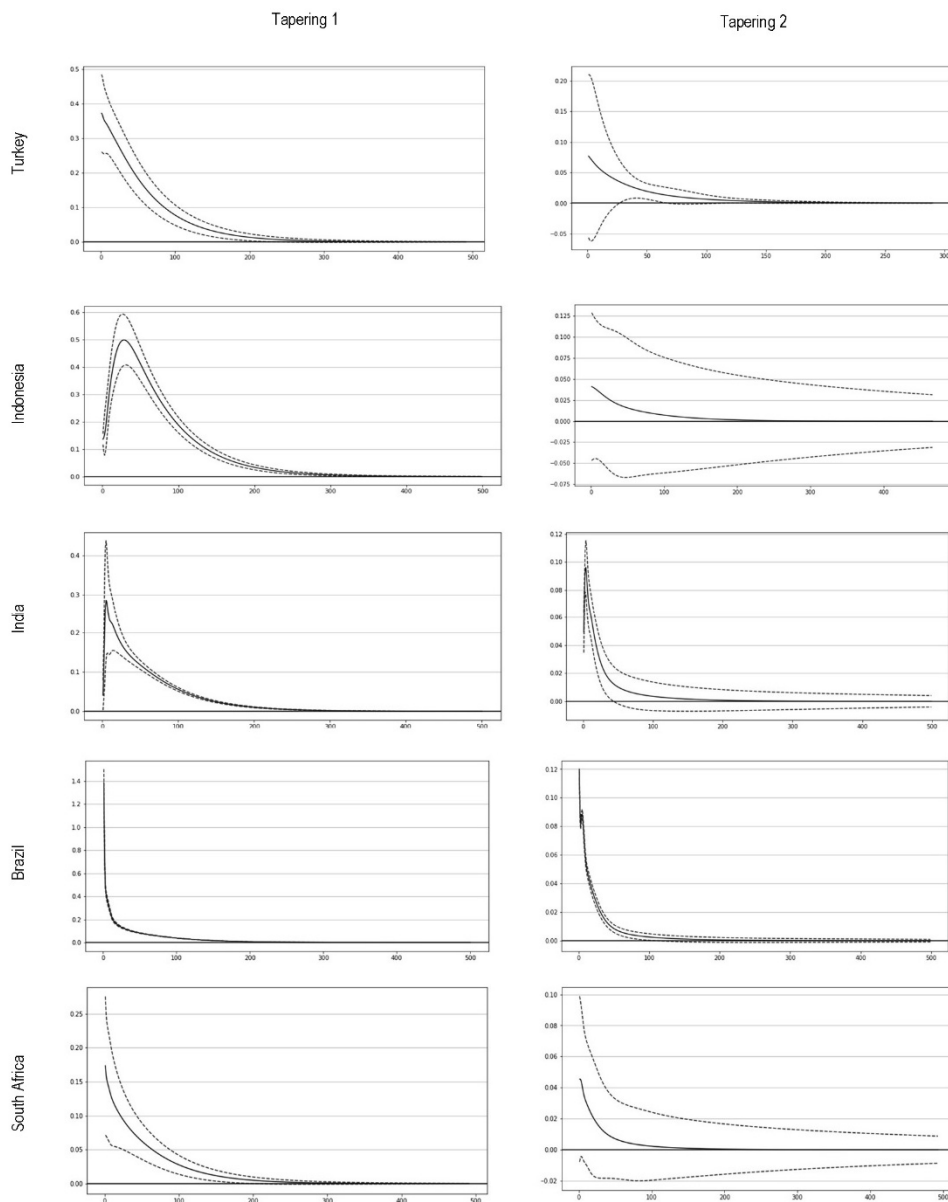
3.2 Volatility Impact from the Past Shocks-Ten-Year Bond Markets

In this section, we present the volatility impulse response functions analysis for the ten-year bond markets. The ten-year bond data for Turkey is not available prior to March 12, 2010. Hence, we consider two historical shocks (Tapering 1 and Tapering 2) that are within the sample period.

3.2.1 Tapering 1

Figure 2 shows the time pattern of the impulse response of volatilities after each historical event. It demonstrates that there are large statistically significant volatility increases stemming from this shock on all five conditional variances after Bernanke's exit signal. This indicates the tapering signal has a significant but different impact on each bond market in the sample. We find that the largest positive impact for this post-signal can be discerned for Brazil's ten-year bond rates. Its one-step ahead expected conditional variance is increased by around 140%. The positive impact for the post-signal on expected conditional variance of ten-year bond rates of Indonesia, Turkey, India and South Africa are about 50%, 37%, 29% and 16%, respectively for the one-step ahead expected conditional variance. Therefore, in terms of the impact (peak), we

have the following ranking for the countries in the sample (from highest to lowest): Brazil > Indonesia > Turkey > India > South Africa.

Source: Authors' own calculations.

Figure 2 Volatility Impulse Responses Functions for Ten-Year Bond Rates with 99% Confidence Intervals

The impact is instantaneous for all countries except Indonesia for which the largest response of conditional variance occurs after 30 days. The results reported above indicate that all five countries' bond rates especially Brazil exhibit a high responsiveness to the shock. These findings may reflect the fact that Brazil's ten-year bond market is much less insulated from shocks relative to other emerging markets. Furthermore, the impacts are relatively perpetuated, although less so than is the case in foreign exchange markets. In other words, the impact of the shock seems to be persistent for all countries as they do not die out after 200 days on average. The reason for this has to do with several eigenvalues of the matrix $A \otimes A + G \otimes G$ being very close to unity.

As a conclusion, the findings suggest that the sensitivity of bond markets to the impact of shocks is largely market-specific despite the fact that the shocks are absorbed by bond markets concurrently. Brazil seems to be more volatile and responsive than the other markets regarding the volatility impulse response analysis associated with Tapering 1. We also find that South Africa is the least sensitive to the shock in terms of size.

3.2.2 Tapering 2

Figure 2 shows that there are statistically significant volatility increases stemming from the Tapering 2 shock on only two conditional variances after the Fed's tapering announcement (i.e., Brazil and India). The size of the impacts is much lower than the Tapering 1 shock. The positive impact for the post-Tapering 2 on expected conditional variance of bond rate return of Brazil and India are about 12% and 9%, respectively for the one-step ahead expected conditional variance. The Tapering 2 shock has significantly much less impact on bond markets than the Tapering 1 shock in terms of size. We also find that the impact steadily vanishes within significantly shorter period than Tapering 1. Again, similar to Tapering 1, while Brazil seems to be more volatile and responsive than the other markets regarding volatility impulse response analysis associated with Tapering 1, Indonesia is the least responsive to the shock in terms of size. To sum up, both the size and persistency of the impact of the shock is much less than for Tapering 1.

Overall, regarding the volatility impulse response analysis in the foreign exchange and bond markets in the *Fragile Five*, we have the following results. First, our findings suggest that Brazil is the most sensitive country among the *Fragile Five* to the shocks under investigation both in the exchange rate and the bond markets. This underscores the fragility of Brazil's financial markets to such shocks. Second, in terms of size, we observe that shocks specifically Tapering 1 and Tapering 2 seem to have a more impact on the bond markets than on the exchange rate markets. As a result, we can infer that the Fed's tapering decision affects bond markets more than exchange rate markets. This result might be attributable to the fact that during the taper tantrum, foreign investors have gradually increased their share in bond markets of emerging economies. Surges in foreign ownership in turn make bond rates more responsive to global shocks. These results are consistent with David Bowman, Juan M. Londono, and Horacio Sapriza (2015) and Yildirim (2016).

4. Estimation Results - Dynamic Conditional Correlations

4.1 Foreign Exchange Markets

Table 3 presents the estimation results of the AR (1) - FIAPARCH (1, d, 1) - DCC model for exchange rates. We find that most of the coefficients are significant and except for the asymmetry term (γ), all coefficients have expected sign. Positive and insignificant coefficients (γ) of asymmetry terms indicate the absence of leverage effects.

Furthermore, the condition that conditional variances are positive is satisfied for all models. The long memory coefficients (d) are also significant at 5 % and 1 % level of significance suggesting that exchange rate volatilities are persistent. The power term coefficients (δ) are all positive and significantly different from 2 confirming the appropriateness of the FIAPARCH model in our analysis.

Table 3 Estimation Results for Exchange Rates

	Turkey	India	Indonesia	South Africa	Brazil
Panel A: Estimates of AR (1) - FIAPARCH (1, d, 1) model					
Constant (mean)	0.000265***	0.000005	0.0002386**	0.000391**	0.000002
	(0.00013)	(0.00004364)	(0.00009672)	(0.00018)	(0.00014)
AR (1)	0.039242*	0.034713***	-0.103713***	0.029680**	0.023410
	(0.02311)	(0.0105345)	(0.02851)	(0.01501)	(0.02127)
Constant (variance)	76.955990	742.416303	0.142372	0.075369	0.602876
	(150.6576)	(1034.5678)	(0.42611)	(0.11857)	(0.65081)
d-FIAPARCH	0.398273***	0.131962***	0.384862***	0.173009**	0.482910***
	(0.08444)	(0.0044932)	(0.09374)	(0.077309)	(0.08742)
ARCH	0.219145***	0.070532*	0.169365*	0.155374*	0.102743*
	(0.07793)	(0.040571)	(0.09200)	(0.09226)	(0.07028)
GARCH	0.516524***	0.956602***	0.688974***	0.289837**	0.508357***
	(0.10578)	(0.18071)	(0.00943)	(0.12141)	(0.12014)
APARCH (γ)	-0.352438	-0.646449	-0.263941	-0.537750	-0.365793
	(0.25391)	(0.58920)	(0.22262)	(0.52455)	(0.29069)
APARCH (δ)	1.512374***	1.364211**	1.716748***	1.9160463***	1.552885***
	0.36830	0.65047	0.28910	0.31544	0.20507
Panel B: Estimates of the DCC model					
ρ TURKEY-BRAZIL	0.560481***				
	(0.036165)				
ρ TURKEY-INDONESIA	0.361130***				
	(0.046280)				
ρ TURKEY-S.AFRICA	0.700488***				
	(0.030751)				
ρ TURKEY-INDIA	0.453308***				
	(0.038715)				
ρBRAZIL-INDONESIA	0.307048***				
	(0.048258)				
ρBRAZIL-S.AFRICA	0.532914***				
	(0.033211)				

$\rho_{\text{BRAZIL-INDIA}}$	0.386405*** (0.039642)			
$\rho_{\text{INDONESIA-S.AFRICA}}$	0.423755*** (0.047054)			
$\rho_{\text{INDONESIA-INDIA}}$	0.344259*** (0.044933)			
$\rho_{\text{S. AFRICA-INDIA}}$	0.483849*** (0.035913)			
θ	0.011612*** (0.0035807)			
α	0.981512*** (0.0080865)			
Student t df	7.708078*** (0.42048)			

Panel C: Diagnostic tests

$Q^2(50)$ prob.	46.6164 [0.6099549]	65.6278 [0.0681688]	79.6921 [0.0547886]	37.9707 [0.8939009]	37.2441 [0.9091446]
Hosking2 (50)	1195.19 [0.8552019]				
Li-McLeo2 (50)	1196.22 [0.8502811]				
Number of obs.	2569				

Notes: Figures in parentheses and brackets are standard errors and probabilities, respectively.

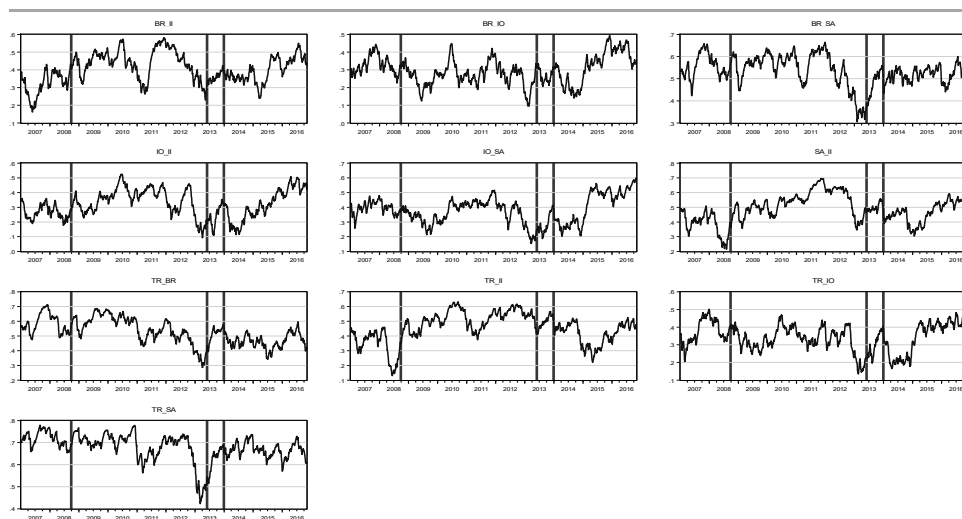**Source:** Authors' own calculations.

As seen from the DCC estimates in Table 3, correlations between exchange rates are positive and statistically significant at 5% or 1% level of significance. The highest average correlation is between the Turkish Lira and the Rand while the lowest one is between the Real and Rupiah. Furthermore θ and α parameters are significant for the DCC model. This implies that the DCC model provides a good fit. On the other hand, the sum of the θ and α parameters is less than unity indicating that conditional correlations are mean reverting.

Diagnostic test results for the AR (1)-FIAPARCH-DCC model are presented at the bottom of Table 3 with probability values of the Ljung-Box $Q^2(50)$, Hosking squared (50) and Li-McLeo squared (50) statistics show that there is no remaining ARCH effect in the residuals.

Figure 3 plots the estimates of dynamic conditional correlations (DCC), which are obtained from AR (1)-FIAPARCH-DCC model, between the exchange rate returns of different country combinations during the period January 2007-November 2016. We have total 10 combinations of the DCC plots since there are five countries in the sample for the exchange rate analysis. We observe that the DCC plots exhibit relatively high and positive correlations for most cases and low but positive correlations in others.

We first consider the estimates of the dynamic conditional correlations (DCC) between the exchange rate returns of Turkey (TR) and those of Brazil (BR), India (II), Indonesia (IO) and South Africa (SA) during the period January 2007-November 2016.

The results suggest that the DCCs increase sharply after both the Lehman bankruptcy and the Tapering shocks. This result is in line with earlier studies (see Table 4 in Itir Ozer-Imer and Ibrahim Ozkan 2014 for a list of studies). The result may be attributable to several factors. Due to their shared macroeconomic characteristics (i.e., after all, they are categorized as emerging markets), large investors in forex markets including international banks might treat them similarly which in turn could cause positive and high correlations between their currencies. During turmoil times participants in FX markets might prefer safer assets and therefore flight to quality behavior tend to increase. In other words, capital flows from relatively risky emerging market assets to safer ones like the US treasuries.

Notes: Lehman Brothers (Sep 15, 2008), Tapering 1 (May 22, 2013) and Tapering 2 (Dec 18, 2013) are shown by the first, second and third lines, respectively. BR - Brazil, IO - Indonesia, II - India, SA - South Africa, TR - Turkey.

Source: Authors' own calculations.

Figure 3 The DCCs for the Exchange Rates

We also find that DCCs for South Africa are systematically larger than those for Brazil, which in turn are larger than those for India. And DCCs for Indonesia exhibit the lowest correlations. Regarding other country combinations, we see similar DCC patterns in the sense that the DCCs increase after the shocks, consistent with the literature. Overall, we also observe relatively high and positive correlations among the exchange rate returns of Turkey, Brazil and South Africa and, to some extent, India. However, the DCCs of Indonesia and those of others are relatively lower. In other words, we can group the sample into two subgroups: (a) Turkey, Brazil, South Africa and India; (b) Indonesia. This might be partly due to the rising influence of China on the Indonesian economy as it serves as Indonesia's the largest export and import market, but also due to specific monetary (policy rate hikes, currency intervention) and fiscal (reduction of energy subsidies etc.) policies of Indonesia (M. Chatib Basri 2017).

4.2 Ten-Year Bond Markets

Table 4 shows the estimation results of the AR (1)-DCC-FIAPARCH(1, d, 1) specification for ten year bond rates. The results are similar to those obtained with exchange rates. Most of the coefficients are significant and except for the leverage coefficient all coefficients have the expected signs. The fractional integration coefficient (d) is significant for all bond markets. Moreover, the power term coefficients (δ) are significantly different from 2 justifying the use of a FIAPARCH specification. The FIAPARCH coefficients satisfy the restrictions shown in Equation (9) indicating that conditional variances are positive. The DCC estimates in Table 4 suggest that the correlation coefficients obtained from the DCC model are significant except for the one between Turkey and India. We also find that the coefficients θ and α are significant and that their sum is less than unity indicating that the conditional coefficients are mean reverting. The insignificant diagnostic test statistics presented at the bottom of the table confirms the appropriateness of the AR (1)-FIAPARCH-DCC model used in the study.

Figure 4 plots the estimates of dynamic conditional correlations (DCC) between the ten-year bond rates of different country combinations during the period January 2010-November 2016. Note that ten-year bond rate data is not available prior to January 2010 for Turkey. We observe that DCC plots exhibit both positive and negative correlations during the sample period.

Our results indicate that the correlations between bond markets are lower than those between foreign exchange markets. For example, while the average of DCCs between ten-year bond rates of Turkey and those of India is 0.02, the average of exchange rate return correlations turns out to be 0.45 (see summary statistics of the DCC series in Tables A1 and A2 in the Appendix). We observe the same differences with other country combinations. This result, which is one of the main findings of our study, suggests that bond markets, at least ten-year bond markets, provide a better diversification opportunity for investors than foreign exchange markets in the emerging markets under investigation. When we consider the dynamic correlations of Turkey with others, we observe that the DCCs between Turkey and South Africa are relatively higher than those with Indonesia, which are in turn higher.

Table 4 Estimation Results for Bond Rates

	Turkey	India	Indonesia	South Africa	Brazil
Panel A: Estimates of AR (1) - FIAPARCH (1, d, 1) model					
Constant (mean)	8.231178***	7.578575***	6.258622***	35.811792***	12.348567***
	(1.0336)	(0.87623)	(0.41389)	(0.96619)	(0.73716)
AR (1)	0.697060***	0.782582***	0.595735***	0.894432***	0.793848***
	(0.002161)	(0.004529)	(0.0011862)	(0.23678)	(0.0024166)
Constant (variance)	0.002447	0.000578	0.001804	0.152408**	0.059252***
	(0.002566)	(0.004125)	(0.0024665)	(0.06345)	(0.017203)
d-FIAPARCH	0.267678**	0.196975***	0.303744***	0.272066***	0.058111
	(0.12327)	(0.006538)	(0.053029)	(0.073246)	(0.086935)
ARCH	0.231153	0.558156***	0.786891***	0.182522	0.305602***
	(0.22015)	(0.032875)	(0.010410)	(0.11562)	(0.12284)

GARCH	0.432549** (0.19009)	0.474217*** (0.12043)	0.983779*** (0.012316)	0.036664*** (0.00238)	0.541806 (0.19913)
APARCH (γ)	-0.240683 (0.23760)	-0.436787 (0.39532)	-0.227042** (0.21519)	-0.809306 (0.82176)	-0.834938 (0.83445)
APARCH (δ)	1.934784*** (0.44394)	1.962360*** (0.48032)	1.809836*** (0.36298)	0.433645*** (0.12603)	1.401716*** (0.21321)

Panel B: Estimates of the DCC model

$\rho_{\text{TURKEY-INDIA}}$	0.012644 (0.027851)
$\rho_{\text{TURKEY-INDONESIA}}$	0.129945*** (0.028091)
$\rho_{\text{TURKEY-S.AFRICA}}$	0.305281*** (0.028465)
$\rho_{\text{TURKEY-BRAZIL}}$	0.131449*** (0.032933)
$\rho_{\text{INDIA-INDONESIA}}$	0.040543** (0.012329)
$\rho_{\text{INDIA-S.AFRICA}}$	0.051080* (0.030847)
$\rho_{\text{INDIA-BRAZIL}}$	0.026950* (0.012342)
$\rho_{\text{INDONESIA-S.AFRICA}}$	0.162641*** (0.030576)
$\rho_{\text{INDONESIA-BRAZIL}}$	0.027498 (0.032521)
$\rho_{\text{S.AFRICA-BRAZIL}}$	0.169821*** (0.040417)
θ	0.007955*** (0.0026816)
α	0.969150*** (0.0099211)
Student t df	4.328344*** (0.15342)

Panel C: Diagnostic tests

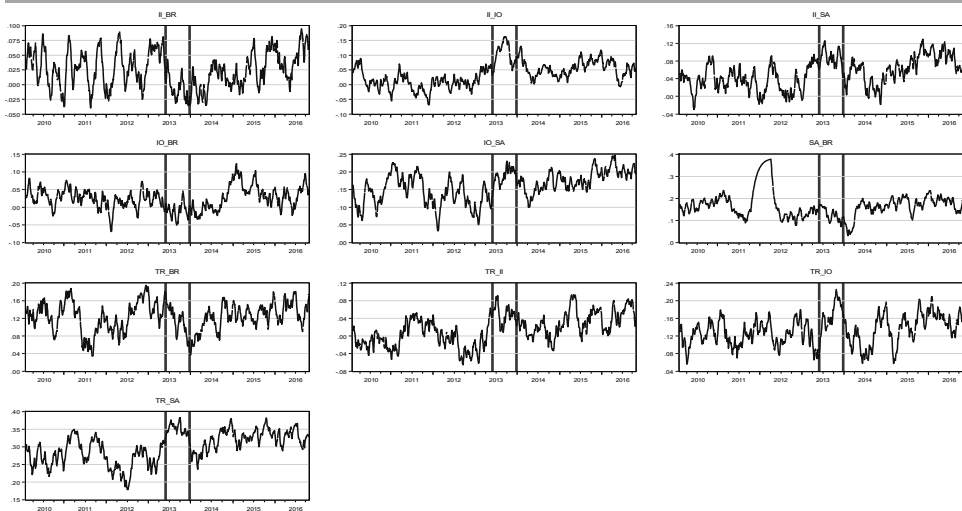|					
$Q^2(50)$	37.9745 [0.8938169]	30.1136 [0.9883557]	62.4691 [0.1109333]	13.6893 [0.9781480]	0.378133 [0.8963521]
Hosking2 (50)	1003.69 [0.9721940]				
Li-McLeod.2(50)	1347.97 [0.5259872]				
Number of obs.	1683				

Notes: Figures in parentheses and brackets are standard errors and probabilities, respectively.

Source: Authors' own calculations.

Than those with Brazil. The DCCs between Turkey and India exhibit lower correlations. Indeed, the DCCs of India with others demonstrate the lowest correlations

overall. In other words, we can infer that the Indian ten-year bond market moves independently from others during the sample period.

To compare the dynamic conditional correlations between the ten-year bond markets and the foreign exchange markets, we conduct mean- and variance-tests. The average correlations in the foreign exchange markets are significantly larger than those in the bond markets. Several factors may explain these patterns. Central banks' coordinating actions concerning exchange rates help increase correlations. Moreover, it might have to do with the fact that the forex market is the largest and the most liquid asset market in the world. Indeed, according to the BIS triennial report of 2016, the average daily trading volume in the foreign exchange market was around 5.1 trillion USD in April 2016. However, average daily trading in global bond markets was around 700 billion USD. And the US Dollar, being the most critical currency, accounts for 85% of forex trading volume (Bank for International Settlements - BIS 2016). Since we measure each currency in our sample against the USD and movements in the value of the USD would automatically lead to appreciation or depreciation in other currencies which in turn cause higher correlations. Unlike the currencies in our sample, bond rates are measured in local currencies rather than USD. Therefore, idiosyncratic domestic factors are more instrumental in determining the sensitivity of bond rates than forex markets to global financial shocks (Fernanda Nechio 2014). Regarding the volatilities (captured by the variance) of the DCC series, the variance-tests suggest that the correlations among the ten-year bond markets exhibit less volatility than the ones among the exchange rate markets. This result may also be attributed to the fact that global exchange rate markets are much larger and more liquid than global bond markets.

Notes: Tapering 1 (May 22, 2013) and Tapering 2 (Dec 18, 2013) are shown by the first and second lines, respectively. BR - Brazil, IO - Indonesia, II - India, SA - South Africa, TR - Turkey.

Source: Authors' own calculations.

Figure 4 DCC for the Ten-Year Bond Rates

5. Conclusion

Different methods have been utilized in the literature to analyze various financial markets focusing on different episodes and country samples including advanced and emerging markets. Results might differ from each other depending on the method and sample used in the analysis. Nonetheless, most of the literature documents significant volatility spillover effects among financial markets. As far as we know, this is the first paper using the FIAPARCH-DCC model and volatility impulse response analysis *a la* Hafner and Herwartz (2006) which examines the volatility spillover effects among the foreign exchange and ten-year bond markets of the emerging economies of the so-called the *Fragile Five*. Through VIRF, we measure not only the size but also the persistence of volatility spillovers of the above-mentioned financial markets. For this purpose, we consider three important historical shocks, the Lehman bankruptcy and two shocks associated with tapering decisions (Bernanke's first tapering signal and the Fed's eventual tapering decision) that have had a tremendous impact on the global financial markets.

Regarding the VIRF analysis of the foreign exchange markets, our results suggest that in terms of both size and persistency the Lehman shock had a more significant impact on the exchange rate volatilities for each country in the *Fragile Five* than both of the tapering events. Between Tapering 1 and Tapering 2, we find that the latter seems to affect exchange markets more than the former. For ten-year bond markets, due to lack of data we exclude some observations prior to January 2010 from the analysis. Focusing on the impact of only the tapering shocks, we find that in contrast with the foreign exchange markets, both the size and persistency of the impact of the Tapering 2 shock is much less than the Tapering 1 shock. We also find that the Fed's tapering decision affects bond markets more than it affects foreign exchange markets in the *Fragile Five*. a significant increase in foreign ownership in bonds of emerging economies during the taper tantrum might explain this result, which is consistent with earlier literature (Bowman, Londono, and Sapriza 2015 and Yildirim 2016).

We also investigate separately the dynamic conditional correlations (DCCs) among the exchange rate and the ten-year bond markets of the *Fragile Five* by employing an AR (1)-FIAPARCH-DCC model. We find that the DCCs of exchange rate returns increase sharply after both the Lehman bankruptcy and the two Tapering shocks. Similarly, those of bond rates increase only slightly or decrease after the two Tapering shocks. Our results also suggest that the DCC series of bond rates exhibit much lower correlations than those associated with exchange rate returns. This might be due to the fact that global exchange rate markets are much larger and more liquid than global bond markets (Nechio 2014). This result provides useful information for investors as it indicates that ten-year bond markets provide a better diversification opportunity than foreign exchange markets in the *Fragile Five*.

The VIRF and DCC results also yield important lessons for central banks and other regulators as to how to devise appropriate measures regarding financial stability. Bond markets overall seem to be more responsive than forex markets to financial shocks. Central banks have several monetary policy instruments to influence the economy. The most commonly used one is targeting of short term interest rates (policy rates) which indirectly determine the long-term interest rates in the economy.

According to the impossible trinity in international finance, it is impossible to have all three of the following simultaneously: (a) free capital flows; (b) a fixed foreign exchange rate; (c) an independent monetary policy (Maurice Obstfeld and Alan M. Taylor 1998). In other words, in the absence of capital controls, there is a trade-off between a fixed exchange rate and independently set interest rates. Our results imply that central banks should be more cautious about interest rates rather than exchange rates when confronted with the trade-off as foreign exchange rates are found to be relatively more stable than long-term interest rates.

Our results also provide a ranking of the *Fragile Five* countries in terms of their resilience to financial shocks. According to the ranking, Brazil seems to be the most fragile country among them. Therefore, Brazilian authorities should be more proactive in curbing instability in its currency and bond yields. The other countries could also assess their own resilience to shocks by comparing their position with others so that they can devise more effective policy measures.

This paper could be extended by analyzing how other historical and hypothetical shocks that may occur in the future would affect the financial markets of the *Fragile Five*. It would also be interesting to examine the determinants of the DCCs among these countries to see the rationale behind the observed correlation patterns because the insights would be very helpful for policy makers and portfolio managers. We would like to address these issues as future research topics as well.
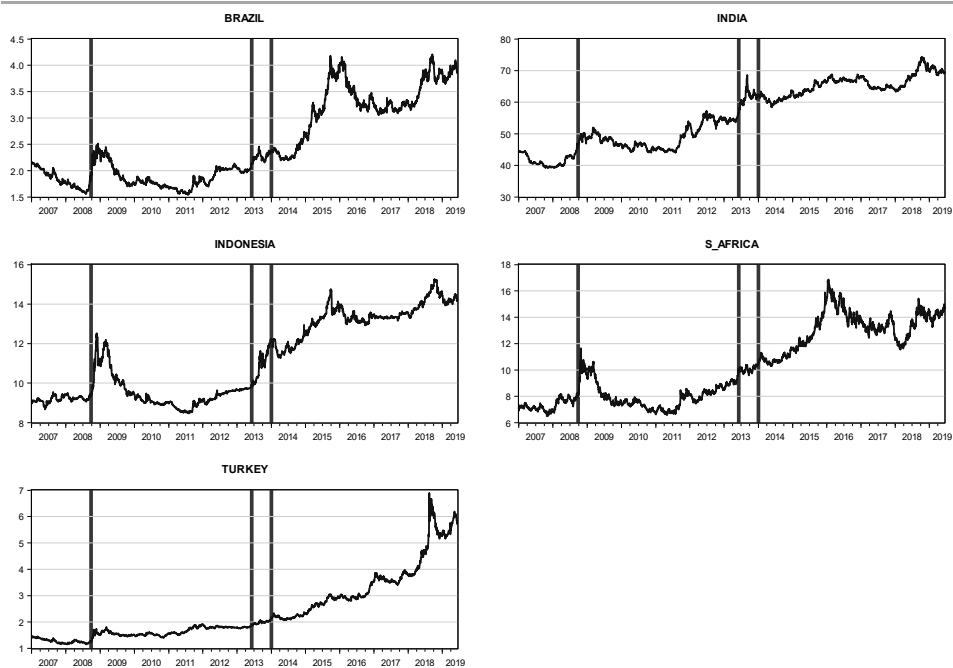
References

Aloui, Riadh, Mohamed Safouane Ben Aïssa, and Duc Khuong Nguyen. 2011. "Global Financial Crisis, Extreme Interdependences, and Contagion Effects: The Role of Economic Structure?" *Journal of Banking & Finance*, 35(1): 130-141. http://dx.doi.org/10.1016/j.jbankfin.2010.07.021

Arouri, Mohamed El Hedi, Amine Lahiani, and Duc Khuong Nguyen. 2015. "World Gold Prices and Stock Returns in China: Insights for Hedging and Diversification Strategies." *Economic Modelling*, 44(C): 273-282. http://dx.doi.org/10.1016/j.econmod.2014.10.030

Baillie, Richard T., Tim Bollerslev, and Hans Ole Mikkelsen. 1996. "Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics*, 74(1): 3-30. http://dx.doi.org/10.1016/S0304-4076(95)01749-6

Bank for International Settlements (BIS). 2016. *Triennial Central Bank Survey: Foreign Exchange Turnover in April 2016*. Basel: BIS - Monetary and Economic Department.

Basri, M. Chatib. 2017. "India and Indonesia: Lessons Learned from the 2013 Taper Tantrum." *Bulletin of Indonesian Economic Studies*, 53(2): 137-160. http://dx.doi.org/10.1080/00074918.2017.1392922

Bauwens, Luc, Sébastien Laurent, and Jeroen V. K. Rombouts. 2006. "Multivariate GARCH Models: A Survey." *Journal of Applied Econometrics*, 21(1): 79-109. http://dx.doi.org/10.1002/jae.842

Beckmann, Joscha, and Robert Czudaj. 2014. "Volatility Transmission in Agricultural Futures Markets." *Economic Modelling*, 36(C): 541-546. http://dx.doi.org/10.1016/j.econmod.2013.09.036

Bollerslev, Tim. 1986. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics*, 31(3): 307-327. http://dx.doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, Tim. 1990. "Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model." *The Review of Economics and Statistics*, 72(3): 498-505. http://dx.doi.org/10.2307/2109358

Bollerslev, Tim, Ray Y. Chou, and Kenneth F. Kroner. 1992. "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence." *Journal of Econometrics*, 52(1-2): 5-59. http://dx.doi.org/10.1016/0304-4076(92)90064-X

Bollerslev, Tim. 2009. "Glossary to ARCH (GARCH)." http://public.econ.duke.edu/~boller/Papers/glossary_arch.pdf.

Bowman, David, Juan M. Londono, and Horacio Sapriza. 2015. "US Unconventional Monetary Policy and Transmission to Emerging Market Economies." *Journal of International Money and Finance*, 55(C): 27-59. http://dx.doi.org/10.1016/j.jimonfin.2015.02.016

Calvo, Guillermo A., and Carmen M. Reinhart. 2002. "Fear of Floating." *The Quarterly Journal of Economics*, 117(2): 379-408. http://dx.doi.org/10.1162/003355302753650274

Christodoulakis, George A., and Stephen E. Satchell. 2002. "Correlated ARCH (CorrARCH): Modelling the Time-Varying Conditional Correlation between Financial Asset Returns." *European Journal of Operational Research*, 139(2): 351-370. http://dx.doi.org/10.1016/S0377-2217(01)00361-7

Conrad, Christian, and Berthold R. Haag. 2006. "Inequality Constraints in the Fractionally Integrated GARCH Model." *Journal of Financial Econometrics*, 4(3): 413-449. http://dx.doi.org/10.1093/jjfinec/nbj015

Conrad, Christian. 2010. "Non-Negativity Conditions for the Hyperbolic GARCH Model." *Journal of Econometrics*, 157(2): 441-457. http://dx.doi.org/10.1016/j.jeconom.2010.03.045

Dimitriou, Dimitrios, Dimitris Kenourgios, and Theodore Simos. 2013. "Global Financial Crisis and Emerging Stock Market Contagion: A Multivariate FIAPARCH-DCC Approach." *International Review of Financial Analysis*, 30(C): 46-56. http://dx.doi.org/10.1016/j.irfa.2013.05.008

Dimitriou, Dimitrios, Dimitris Kenourgios, and Theodore Simos. 2017. "Financial Crises, Exchange Rate Linkages and Uncovered Interest Parity: Evidence from G7 Markets." *Economic Modelling*, 66(C): 112-120. http://dx.doi.org/10.1016/j.econmod.2017.06.003

Ding, Zhuanxin, Clive W. J. Granger, and Robert F. Engle. 1993. "A Long Memory Property of Stock Returns and a New Model." *Journal of Empirical Finance*, 1(1): 83-106. http://dx.doi.org/10.1016/0927-5398(93)90006-D

Engle, Robert F. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica: Journal of the Econometric Society*, 50(4): 987-1007. http://dx.doi.org/10.2307/1912773

Engle, Robert F., and Kenneth F. Kroner. 1995. "Multivariate Simultaneous Generalized ARCH." *Econometric Theory*, 11(1): 122-150. http://dx.doi.org/10.1017/S0266466600009063

Engle, Robert F., and Kevin Sheppard. 2001. "Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH." National Bureau of Economic Research Working Paper 8554.

Engle, Robert. 2002. "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models." *Journal of Business & Economic Statistics*, 20(3): 339-350. http://dx.doi.org/10.1198/073500102288618487

Essaadi, Essahbi, Jamel Jouini, and Wajih Khallouli. 2009. "The Asian Crisis Contagion: A Dynamic Correlation Approach Analysis." *Panoeconomicus*, 56(2): 241-260. http://dx.doi.org/10.2298/PAN0902241E

Giannellis, Nikolaos, Angelos Kanas, and Athanasios P. Papadopoulos. 2010. "Asymmetric Volatility Spillovers between Stock Market and Real Activity: Evidence from the UK and the US." *Panoeconomicus*, 57(4): 429-445. http://dx.doi.org/10.2298/PAN1004429G

Hafner, Christian M., and Helmut Herwartz. 2006. "Volatility Impulse Responses for Multivariate GARCH Models: An Exchange Rate Illustration." *Journal of International Money and Finance*, 25(5): 719-740. http://dx.doi.org/10.1016/j.jimonfin.2006.04.006

Hu, John Wei-Shan, Mei-Yuan Chen, Robert C. W. Fok, and Bwo-Nung Huang. 1997. "Causality in Volatility and Volatility Spillover Effects between US, Japan and Four Equity Markets in the South China Growth Triangular." *Journal of International Financial Markets, Institutions and Money*, 7(4): 351-367. http://dx.doi.org/10.1016/S1042-4431(97)00027-9

Jones, Charles M., Owen Lamont, and Robin L. Lumsdaine. 1998. "Macroeconomic News and Bond Market Volatility." *Journal of Financial Economics*, 47(3): 315-337.

Josifidis, Kosta, Jean-Pierre Allegret, and Emilija Beker Pucar. 2009. "Monetary and Exchange Rate Regimes Changes: The Cases of Poland, Czech Republic, Slovakia and

Republic of Serbia." *Panoeconomicus*, 58(2): 199-226. http://dx.doi.org/10.2298/PAN0902199J

Karanasos, Menelaos, Stavroula Yfanti, and Michail Karoglou. 2016. "Multivariate FIAPARCH Modelling of Financial Markets with Dynamic Correlations in Times of Crisis." *International Review of Financial Analysis*, 45(C): 332-349. http://dx.doi.org/10.1016/j.irfa.2014.09.002

Karanasos, Menelaos, Faek Menla Ali, Zannis Margaronis, and Rajat Nath. 2018. "Modelling Time Varying Volatility Spillovers and Conditional Correlations across Commodity Metal Futures." *International Review of Financial Analysis*, 57(C): 246-256. http://dx.doi.org/10.1016/j.irfa.2017.11.003

Kočenda, Evžen, and Michala Moravcová. 2019. "Exchange Rate Comovements, Hedging and Volatility Spillovers on New EU Forex Markets." *Journal of International Financial Markets, Institutions and Money*, 58(C): 42-64. http://dx.doi.org/10.1016/j.intfin.2018.09.009

Lim, Edward S., John G. Gallo, and Peggy E. Swanson. 1998. "The Relationship between International Bond Markets and International Stock Markets." *International Review of Financial Analysis*, 7(2): 181-190. http://dx.doi.org/10.1016/S1057-5219(99)80034-9

Mensi, Walid, Shawkat Hammoudeh, Duc Khuong Nguyen, and Sang Hoon Kang. 2016. "Global Financial Crisis and Spillover Effects among the US and BRICS Stock Markets." *International Review of Economics & Finance*, 42(C): 257-276. http://dx.doi.org/10.1016/j.iref.2015.11.005

Mensi, Walid, Shawkat Hammoudeh, and Sang Hoon Kang. 2017. "Dynamic Linkages between Developed and BRICS Stock Markets: Portfolio Risk Analysis." *Finance Research Letters*, 21(C): 26-33. http://dx.doi.org/10.1016/j.frl.2016.11.016

Mishra, Prachi, Kenji Moriyama, Papa N'Diaye, and Lam Nguyen. 2014. "Impact of FED Tapering Announcements on Emerging Markets." International Monetary Fund Working Paper 14-109.

Nechio, Fernanda. 2014. "Fed Tapering News and Emerging Markets." *Economic Letters*, March 03. https://www.frbsf.org/economic-research/publications/economic-letter/2014/march/federal-reserve-tapering-emerging-markets/.

Obstfeld, Maurice, and Alan M. Taylor. 1998. "The Great Depression as a Watershed: International Capital Mobility over the Long Run." *The Defining Moment: The Great Depression and the American Economy in the Twentieth Century*. Chicago: University of Chicago Press.

Obstfeld, Maurice, and Alan M. Taylor. 1998. "The Great Depression as a Watershed: International Capital Mobility over the Long Run." National Bureau of Economic Research Working Paper 5960. http://dx.doi.org/10.3386/w5960

Ozer-Imer, Itir, and Ibrahim Ozkan. 2014. "An Empirical Analysis of Currency Volatilities during the Recent Global Financial Crisis." *Economic Modelling*, 43(C): 394-406. http://dx.doi.org/10.1016/j.econmod.2014.09.008

Ribeiro, Pedro Pires, and José Dias Curto. 2017. "Volatility Spillover Effects in Interbank Money Markets." *Review of World Economics*, 153(1): 105-136. http://dx.doi.org/10.1007/s10290-016-0268-7

Sensoy, Ahmet, Duc Khuong Nguyen, Ahmed Rostom, and Erk Hacihasanoglu. 2018. "Dynamic Integration and Network Structure of the EMU Sovereign Bond Markets." *Annals of Operations Research*, 281(1): 1-18. http://dx.doi.org/10.1007/s10479-018-2831-1

Skintzi, Vasiliki D., and Apostolos N. Refenes. 2006. "Volatility Spillovers and Dynamic Correlation in European Bond Markets." *Journal of International Financial Markets, Institutions and Money*, 16(1): 23-40. http://dx.doi.org/10.1016/j.intfin.2004.12.003

Yildirim, Zekeriya. 2016. "Global Financial Conditions and Asset Markets: Evidence from Fragile Emerging Economies." *Economic Modelling*, 57(C): 208-220. http://dx.doi.org/10.1016/j.econmod.2016.04.018
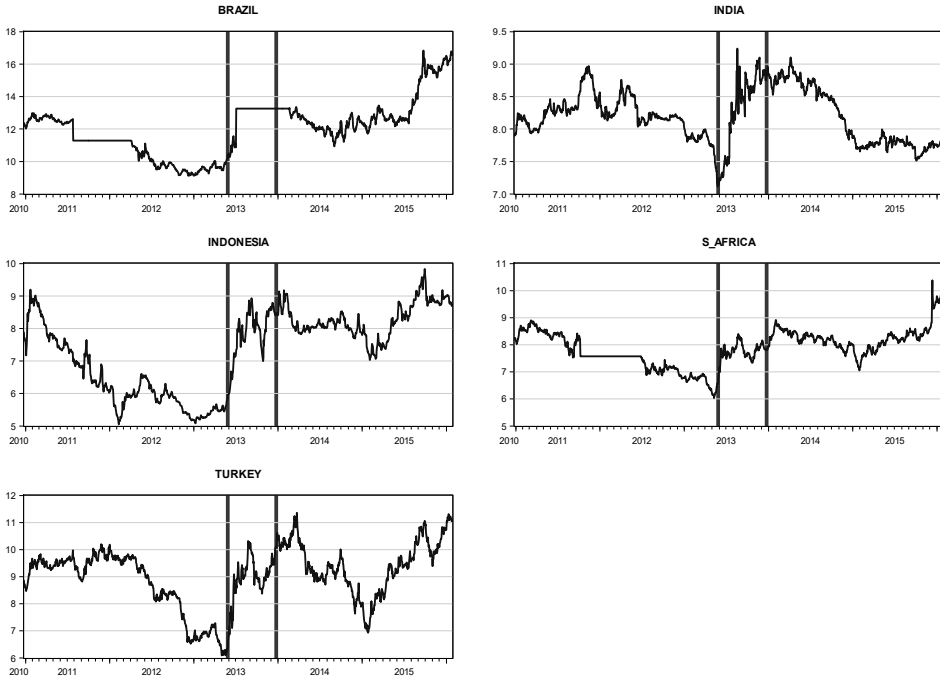
Appendix

Notes: Lehman Brothers (Sep 15, 2008), Tapering 1 (May 22, 2013) and Tapering 2 (Dec 18, 2013) are shown by the first, second and third lines, respectively.

Source: Authors' own calculations.

Figure A1 Exchange Rates

Notes: Tapering 1 (May 22, 2013) and Tapering 2 (Dec 18, 2013) are shown by the first and second lines, respectively.

Source: Authors' own calculations.

Figure A2 Ten-Year Bond Rates

Table A1 Descriptive Statistics for the DCCs between Exchange Rates

	TR_BR	TR_IO	TR_SA	TR_II	BR_IO	BR_SA	BR_II	IO_SA	IO_II	SA_II
Mean	0.53	0.34	0.68	0.45	0.30	0.53	0.40	0.38	0.32	0.49
Median	0.53	0.35	0.69	0.47	0.29	0.54	0.40	0.39	0.32	0.49
Maximum	0.71	0.50	0.78	0.63	0.49	0.67	0.58	0.60	0.53	0.70
Minimum	0.29	0.13	0.42	0.13	0.10	0.30	0.16	0.15	0.09	0.21
Std. dev.	0.09	0.08	0.06	0.10	0.08	0.07	0.09	0.09	0.09	0.09
Skewness	-0.09	-0.44	-1.43	-0.71	0.10	-0.70	-0.14	-0.07	-0.07	-0.19
Kurtosis	2.51	2.48	5.96	3.43	2.75	3.69	2.57	2.42	2.29	2.92
Jarque-Bera	29.4	112.6	1818.3	236.6	11.1	262.4	27.7	38.4	55.6	16.4
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	1357	878	1744	1167	763	1373	1035	977	820	1247
S. sq. dev.	19.35	15.81	9.36	25.65	15.38	11.73	18.79	21.58	22.36	22.65
Observ.	2569	2569	2569	2569	2569	2569	2569	2569	2569	2569

Notes: BR - Brazil, IO - Indonesia, II - India, TR - Turkey, SA - South Africa.

Source: Authors' own calculations.

Table A2 Descriptive Statistics for the DCCs between Ten-Year Bond Rates

	TR_BR	TR_IO	TR_SA	TR_II	BR_IO	BR_SA	BR_II	IO_SA	IO_II	SA_II
Mean	0.12	0.13	0.30	0.02	0.02	0.17	0.02	0.16	0.04	0.05
Median	0.13	0.13	0.31	0.02	0.02	0.16	0.02	0.17	0.04	0.05
Maximum	0.19	0.23	0.38	0.09	0.12	0.38	0.09	0.25	0.16	0.13
Minimum	0.03	0.06	0.18	-0.07	-0.07	0.03	-0.04	0.03	-0.07	-0.03
Std. dev.	0.03	0.03	0.04	0.03	0.03	0.06	0.03	0.04	0.04	0.03
Skewness	-0.38	-0.02	-0.45	0.02	0.15	1.37	0.08	-0.49	0.37	-0.04
Kurtosis	2.75	2.56	2.51	2.36	3.13	6.14	2.12	2.75	3.06	2.29
Jarque-Bera	44.84	13.94	74.12	28.93	7.36	1218.9	56.58	70.55	38.41	36.19
Probability	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Sum	207.61	224.20	506.04	26.53	40.41	283.35	41.22	269.64	63.36	88.78
S. sq. dev.	1.77	1.84	3.09	2.02	1.63	6.13	1.59	2.89	3.04	1.88
Observ.	1683	1683	1683	1683	1683	1683	1683	1683	1683	1683

Notes: BR - Brazil, IO - Indonesia, II - India, TR - Turkey, SA - South Africa.

Source: Authors' own calculations.

THIS PAGE INTENTIONALLY LEFT BLANK