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Asymmetric Linkages among the Fear Index and Emerging market Volatility Indices

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ABSTRACT

This study explores the relationships between changes in the fear index (VIX) and changes in emerging market volatilities i.e., Chinese, Brazilian and the overall emerging volatility index, across their conditional distributions by employing a mixed Quantile regression - Copula methodological approach. Moreover, we analyze whether emerging market volatility indices would respond asymmetrically to positive and negative volatility shocks in the fear index i.e., whether the relationships are asymmetric between the VIX and the emerging market volatilities. Our results confirm that there are strong positive relationships between changes in the VIX and emerging market volatilities, and the linkages tend to be stronger for the upper-parts of the conditional distributions, namely above the median-quantiles up to the extreme-quantiles. In all cases, the nature of the relationship appears to be contemporaneous and on average is three times stronger than their lagged relationship. Further test results reveal that the relationship is highly asymmetric i.e., the effect of a positive shock in the VIX is on average about twice more pronounced than the effect of a negative shock at the extreme-tails of their conditional distributions, a stylized fact that cannot be revealed via conventional estimation methods as OLS. If we compare the effects of positive and negative VIX shocks on emerging market volatilities utilizing QRM, Copulas and OLS, our findings reveal that the effect of a positive shock by the QRM at the 95% quantile is about eight times higher than the one revealed by OLS. An exhaustive robustness analysis is also performed with respect to other volatility measures.

JEL Codes: C32, C58, G10, G17
Keywords: Emerging markets; IV spillovers, VIX; Quantile regression; Copulas

1. INTRODUCTION

Due to the integration of economies through trade and investment flows, stock markets' links have been increasing over the last three decades, which in turn led to considerable increases in correlations among global equities. The latter effect, particularly among the developed economies, has decreased the benefits of diversification available to international investors (Bekaert and Harvey, 2014; Badshah, 2016). However, empirical evidence shows that the emerging markets present lower correlations with equities from the developed markets, yield higher returns and demonstrate higher risks (Bekaert *et al.*, 2011; Bekaert and Harvey, 2014). Furthermore, it is reported that the dynamics of market integration via spillovers are revealed much faster through stock market volatilities rather than stock market returns (Peng and Ng, 2012). We therefore use 2^{nd} moment measures for the US, China, Brazil, and emerging markets to investigate cross-market relationships and their asymmetries. Emerging markets are heavily linked to the U.S market through underlying trade and investment channels. As such, a shock in the US is transmitted to the emerging markets considering that it impacts exports and investments made by US multinationals in emerging economies. Thereby emerging volatility indices should respond to a volatility shock originated in the US hence the direction of the spillovers should be largely from the US toward the emerging markets.

We employ implied volatility index as a proxy for market volatility; it reflects investors' expectations about future market volatility better and faster than the realized volatility. It is also documented that the information content of implied volatility is superior versus any other volatility measure (Blair *et al*, 2001; Poon and Granger, 2003). The implied volatility index is found to be countercyclical as on average it is high during recessions and lower during expansions. The increases in implied volatility are attributed to the effect of leverage, i.e., in particular during recessions firms usually take on more debt and augment their return volatility (Bloom, 2014). Another explanation for the high market volatility during recessions might be attributed to investor risk aversion, which in turn increases the prices of put options (Bollerslev *et al.*, 2009; Bekaert *et al.*, 2013; Bloom, 2014).

We rely on the forward-looking volatility indices, namely the VIX, VXEEM, VXFXI, and VXEWZ which reflect the US uncertainty, the overall emerging stock market fear gauge, the Chinese stock market volatility, and the Brazilian stock market anxiety respectively. The Chicago Board of Options Exchange (CBOE) has launched the VXEEM for emerging stock markets, while VXFXI is introduced by the Chinese market, and the VXEWZ by the Brazilian stock market on March 16, 2011. VXEEM is calculated from the cross-section of options traded on the underlying iShares MSCI Emerging markets ETF (which provides exposure to twenty-six emerging markets), the VXFXI is estimated from the options traded on the underlying FTSE China index ETF, and the VXEWZ is implied from the iShares MSCI Brazil index ETF. However, using volatility index changes rather than underlying stock market returns incorporates significant challenges as variations in volatility changes are much higher than the ones in returns. As reported by Low (2004), Peng and Ng (2014) and Badshah (2013), volatility changes are non-normal and asymmetrically distributed. Additionally, China and Brazil heavily rely on their exports to the U.S and capital inflows by U.S multinationals. A shock in the U.S stock market which may lead to a decline in consumer confidence or even to recession, may spillover to emerging economies due to the underlying channels of trade and investments, or vice versa in case of a positive shock in the U.S market. The implied volatility indices reflect these shocks, thus they are considered "informed measures".[1] Fear index and emerging market volatilities may exhibit an asymmetric dependence structure, in that their relationship can be higher during recessionary conditions and lower during expansionary periods. Consequently, capturing asymmetry may be of

[1] Whaley (2000, 2009) dubbed the VIX index as the investors' fear gauge.

paramount importance for international portfolio investors in order to avoid suboptimal diversification (Peng and Ng, 2012).

We use quantile regressions and time-varying asymmetric copula methods to examine the contemporaneous relationships and asymmetries between changes in the VIX and changes in the emerging market volatility indices. A stream of recent literature provides empirical evidence on market integration and volatility spillover effects across developed markets, mainly among the US and European economies (Nikkinen and Sahlström 2004; Skiadopoulos 2004; Nikkinen *et al.*, 2006; Äjiö 2008; Jiang *et al.*, 2012; Peng and Ng, 2012; Kenourgios, 2014). In particular, Äijö (2008) investigates volatility linkages between European indices (VDAX, VSMI and VSTOXX) and finds that implied volatility indices are highly correlated and vary over time, with the VDAX being the dominant source of volatility information diffusion. VDAX can explain the variance of forecast errors for the VSTOXX and VSMI at the level of 65% and 35% respectively. Nikkinen and Sahlström (2004) study the degree of market integration between the US, UK, German and Finnish stock markets using implied volatility indices. Similarly, they report a high degree of integration among these markets; interestingly while the US market is the leading source of information transmission to other markets, within the European context the German market leads other European economies. Moreover, Jiang *et al.* (2012) investigates the implied volatility linkages between the US and many European stock markets. They find significant spillovers between them and within European markets and they provide evidence of volatility contagion across markets during the global financial crisis. Peng and Ng (2012) study the inter-dependence among five major US, European and Japanese volatility indices (i.e., VIX, VXN,VDAX, VFTSE, and VXJ) and show that they are highly correlated, whilst their dependence structure affected by financial shocks reveals a faster response to information than their underlying stock markets. Kenourgios (2014) studies the volatility contagion across US and European indices namely between VIX, VCAC, VDAX, VFTSE and VSMI using the asymmetric dynamic conditional correlation GARCH model of Cappiello *et al.* (2006) and demonstrates that their correlation is time-varying and increases considerably during crisis periods. Lastly, Badshah (2016) investigates volatility linkages among the VIX, VXEFA and VXEEM by employing a VAR-DCC-GARCH model and shows strong spillover effects from the fear index to both VXEFA and VXEEM.

Diebold and Yilmaz (2009) propose a new method based on forecast error variance decompositions from vector autoregressions (VAR) to capture the extent of volatility spillovers from one market to another market, which is called DY spillover index. Diebold and Yilmaz (2012, 2014) extend the methodology by using generalized VAR framework in which forecast error variance decomposition are invariant to the ordering of variables in the system. However, the DY methodology is unable to distinguish the asymmetry in spillovers as that can originates due to bad and good volatility shocks. Segal *et al.* (2015) characterize bad volatility as the volatility that is related to the negative innovations to the overall output, returns and good volatility is related to the positive innovations to these variables. Barunik *et al.* (2016) use semivariance measure of Barndorff-Nielsen *et al.* (2010) which is based on the realized variance i.e. decomposing realized variance into negative and positive volatilities (good and bad volatilities). Then they combine with the DY methodology to monitor asymmetric spillovers at the US sectoral level before, during and after the global financial crises.

Our study builds upon the aforementioned literature, yet it differs in three aspects; firstly, we study volatility spillovers from the US stock market, to Chinese, Brazilian and overall emerging markets indices. To our knowledge, our study is the first to investigate those transmission mechanisms using data from the above newly introduced CBOE implied volatility indices. Secondly, we consider a quantile regression (QR) approach as it allows examination of co-movement in specific market circumstances, including bearish (lower quantile), bullish (upper quantile) and normal (intermediate quantile) markets that other models (e.g., DY models, and Barunik *et al.* 2016) are unable to capture. Thirdly, we utilize a time-varying asymmetric copula methodology to capture time-variations in the dependence structure at extreme-quantiles and infer upon their linear correlations or nonlinear linkages, as DY spillover index and Barunik *et al.* (2016) are unable to capture the tail dependence.

Our main findings suggest a strong contemporaneous relationship between changes in the VIX fear index and changes in the emerging market volatility indices of China, Brazil and the overall emerging markets measure. The dependencies are stronger at the upper-tails of the conditional distributions, particularly at the extreme-tails over 95% quantiles. The links present a more pronounced contemporaneous nature than a lagged one, with the contemporaneous relationship being more than 3 times stronger than the one-lagged one. Importantly, the relationship is asymmetric: at the 95% quantile the effect of a positive change in the VIX is twice as higher as the effect of a negative change on the emerging market volatility, which conventional methods fail to detect. Specifically, when we compare the effect of a positive and/or negative VIX shock upon emerging market volatilities using QRM, we find the effect of a positive shock by the QRM at the 95% quantile being about 8 times higher than the one revealed by conventional OLS. Finally, comparing the magnitude of the contemporaneous relationships of the fear index vis-à-vis all other three volatility indices at extreme tails, we reveal that the overall emerging market volatility is strongly related to the US followed by the Chinese stress index, and lastly by the Brazilian market. At the same time, if we compare the asymmetric responses of the three volatility indices regarding positive shocks versus negative shocks in the VIX, we show that the absolute difference is the highest for the Chinese market followed by the overall emerging market index, and then by the Brazilian market; the latter empirical conclusion suggests that Chinese investors are more sensitive to changes in the VIX.

The organization of the paper is as follows: in section 2 we discuss the data while in section 3 we present our novel methodology. In section 4 we provide an exhaustive analysis of our empirical findings while in section 5 we provide further robustness tests. Finally, Section 6 concludes.

2. Data and Preliminary Analysis

We use daily data on the VIX, VXEEM, VXFXI, and VXEWZ obtained from the Chicago Board of Option Exchange for the sample period March 16, 2011 to January 16, 2016. The CBOE introduced the VIX in September 2003, which is computed by the bid and ask prices from the cross-section of S&P 500 options.[2] On March 16, 2011, the CBOE also introduced three volatility indices, i.e., the VXEEM for all emerging stock markets, the VXFXI for the Chinese market and the VXEWZ for the Brazilian equity market.[3] The VXEEM is computed from options traded on the underlying iShare MSCI ETF which incorporates up to 26 emerging stock markets. The VXFXI is calculated from options traded on the underlying FTSE ETF China index, and lastly the VXEWZ is implied from the iShares MSCI Brazil ETF index. Using model-free methodologies similarly to VIX, the VXEEM, VXFXI and VXEWZ are estimated from the bid and ask prices of the underlying options for the iShares MSCI Emerging Markets, FTSE China and iShares MSCI Brazil index ETF, respectively. It is important to note that all options (S&P 500, emerging ETF, Chinese and Brazil ETFs) are traded the same hours on the CBOE platform. Thus, our data are not subject to trading time differences.

[2] More details can be found at www.cboe.com/vix
[3] More details can be found at www.cboe.com/vxeem; www.cboe.com/vxfxi; www.cboe.com/vxewz

Figure 1 shows the time series plots of the daily closing levels (%) of the four implied volatility indices from March 16, 2011 to January 16, 2016. Among the four volatility indices, the VXEWZ presents the highest volatility throughout our period, whereas the VIX shows the lowest fluctuations. At the later part of 2011, considerably high volatility levels are observed due to the European debt crisis. However, from 2012 onward until the end of September 2014, volatility remains relatively stable. On October 20^{th}, 2014, the Brazilian volatility spikes to a historical high level of 73%, which reflects the uncertainty just before the second-round runoff of the presidential elections in Brazil. On August 24^{th}, while the Chinese stock market falls about 8.5% (Chinese Black-Monday) causing a worldwide equity market fall, a spike of 58% can be seen on the VXFXI that day, a spike of 55% in the VXEEM, 52% for the VXEWZ and a rise of 40% in the VIX levels. These high volatility levels continue up until January 2016.

Table 1 reports the summary statistics for the VIX, VXEEM, VXFXI and VXEWZ. Panel A of Table 1 presents the statistics for the volatility levels. On average VXEWZ has the highest mean value followed by VXFXI, VXEEM and VIX. During our sample period, the maximum level of VXEWZ is about 73%, for the VXEEM about 64%, for the VXFXI 63% and for the VIX around 48%. All four volatility indices are positively skewed and present excess kurtosis. The reported first order autocorrelations show that all indices are highly persistent. The Augmented Dickey Fuller (ADF) tests on the levels, reject the null hypothesis of unit root for all volatility indices. Panel B displays the statistics for the log-changes. The mean values are approximately zero, however there are dispersions on a daily basis as it can be observed from the max, min and standard deviations. All indices are positively skewed except the VXEWZ, which suggests that big positive changes occur more frequently than large negative changes and vice versa only for the VXEWZ. All four volatility indices show excess kurtosis and based on the ADF test we reject the null hypothesis of a unit root at 1% level.

3. Methodology

We employ a combined quantile regression time-varying asymmetric copula methodology to model volatility interrelationships and asymmetries in their dependence structure.

3.1 Quantile regression modeling

The quantile regression model (QRM) is implemented to quantify the relationships among the volatility indices. Aside from Baur and Schulze (2005), all previous studies have employed regression models albeit they focus on the average relation (i.e., at the mean of the distribution) between stock market returns and stock volatility. Due to the inherent heterogeneity in stock markets, the linkages between markets returns and volatility might vary across their conditional distributions. Heterogeneity is usually higher during crisis periods or under volatile market conditions. Consequently, traditional approaches which capture the relationship at the mean might lead to misspecification. Importantly, the relationship in the upper-tails might be more important for investors and policy makers. Moreover, the QRM requires weaker distributional assumptions, while it provides a more robust method of modelling return conditionalities, it is less sensitive to outliers and it is well-suited for skewed and leptokurtic distributions exactly as exposed in case of volatility changes.

Before specifying the QRM model for the contemporaneous relationships between changes in the fear index and changes in the emerging market volatility indices, the benchmark mean regression model (MRM) has the following form:

$$\Delta VI_{it} = \alpha + \beta_i \Delta VI_{it-1} + \sum_{0}^{2} \gamma_L \Delta VIX_{t-L} + \delta_L |\Delta VIX_t| + u_t \qquad (1)$$

where α is the intercept, β is the coefficient for the lagged ΔVI_i and i represents the emerging market volatility index. The γ coefficients for ΔVIX incorporate lags of L ranging from 0 to 2. The δ coefficient for the absolute changes in VIX, reflects the effect of size of changes in the VIX. Similarly to the MRM model of Eq. (1), the q^{th} QRM for examining the contemporaneous relationship between changes in the fear index and changes in the emerging market volatility indices has the form:

$$\Delta VI_{it} = \alpha^{(q)} + \beta_i^{(q)} \Delta VI_{it-1} + \sum_{0}^{2} \gamma_{(L)}^{(q)} \Delta VIX_{t-L} + \delta^{(q)} |\Delta VIX_t| + u_t \qquad (2)$$

where $\alpha^{(q)}$ is the intercept, and $\beta_i^{(q)}$ is the coefficient for lagged ΔVI_i. The parameters $\gamma_{(L)}^{(q)}$ depict the coefficients for ΔVIX and $\delta^{(q)}$ for the absolute changes in VIX. The joint coefficients [$\gamma_{(0)}^{(q)}$+$\delta^{(q)}$] and [$\gamma_{(0)}^{(q)} - \delta^{(q)}$] represent the asymmetric effects of positive and negative changes in the fear index. These values will reveal if the emerging market volatility indices respond in symmetric or asymmetric patterns to positive and negative shocks of the fear index. The residuals u_t are assumed to be independent and derived from the error distribution $\emptyset_q(u_t)$ with the q^{th} quantile equal to zero. The main feature of the QRM is that the conditional effects of the changes in the independent variables that are measured by $\beta_i^{(q)}$, $\gamma_{(L)}^{(q)}$, and $\delta^{(q)}$, are functions of the quantile parameter $q \in (0,1)$. We estimate the QRM in Eq. (2) using the method proposed by Koenker and Bassett (1978).

3.2 Time-varying Copula approach

In order to detect second-moment spillover effects, we consider producing parameter estimates of the marginal distributions for the VIX, VXEEM, VXFXI, and VXEWZ via GARCH-filtering. We select the GJR-GARCH (1,1) as the best-suited second-moment model[4] for the VIX, VXEEM, VXFXI, and VXEWZ as also proposed by Glosten, Jagannathan and Runkle (1993). It incorporates the leverage effect so as to model asymmetric volatility stylized distributional characteristics. The GJR model is an extension of the GARCH model, with an additional term added to capture possible asymmetries:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \qquad (3)$$

where $I_{t-1}=1$ if $\varepsilon_{t-1}<0$ and otherwise $I_{t-1}=0$. According to Glosten *et al*. (1993) the positivity and stationarity of the volatility process is guaranteed whenever the parameters satisfy the constraints $\omega>0$, α, β, $\gamma\geq 0$, and $\gamma+(\alpha+\beta)/2<1$. Moreover, we assume that the error term follows a Skewed-*t* distribution to account for clustering tails. We account for time-varying dependence structure by allowing the copula parameters to be time-varying with dynamics described in an evolution equation. For Gaussian and Student-*t* copulas we describe the dynamics of the linear dependence parameter as evolving over time according to the model proposed by Patton (2006):

$$\rho_t = \Omega(\Psi_0 + \Psi_0\rho_{t-1} + \Psi_2 \frac{1}{10}\sum_{j=1}^{10} \Phi^{-1}\left(u_{t-j}\right).\Phi^{-1}(v_{t-j}) \qquad (4)$$

where Ω denotes the logistic transformation $\Omega(x) = (1-e^{-x})(1-e^{-x})^{-1}(x)$ used to keep ρ_t within (-1,1). For the Student-*t* copula, $\Phi^{-1}(x)$ is substituted by $t^{-1}_{v}(x)$. For the conditional Gumbel copula and its rotation, the evolution of δ specified follows an ARMA (1, 10) process given by:

$$d_t = (\Psi_0 + \Psi_0 d_{t-1} + \Psi_2 \frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j} - v_{t-j}\right| \qquad (5)$$

For the SJC copula, the evolution of the upper and lower tail dependence is given by an ARMA (1,10) process as follows:

$$\tau_{U,t}^{SJC} = \Omega\left[\Psi_0^U + \Psi_1^U\tau_{U,t-1}^{SJC} + \Psi_2^U \frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j} - v_{t-j}\right|\right] \qquad (6)$$

[4] As the choice of the most suitable GARCH-type model specification appears to be challenging task, we considered some standard competing models with various lag structures: GARCH, EGARCH, GJR-GARCH and FIGARCH. Based on the *Log (L)* and *SIC* criteria, we choose the best fitted model. The detailed results are available upon request.

$$\tau_{L,t}^{SJC} = \Omega\left[\Psi_0^L + \Psi_1^L \tau_{U,t-1}^{SJC} + \Psi_2^L \frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j} - v_{t-j}\right|\right]. \qquad (7)$$

4. Empirical Results and Discussion

We present the empirical results from the quantile regression analysis while OLS is used as a benchmark. Furthermore, in order to detect time variation in the dependence among the volatility indices we demonstrate the results for asymmetric time-varying copula models with respect to the highest and lowest quantiles temporally.

4.1 Volatility linkages between the fear index and the overall emerging market index

Table 2 reports the results for the quantile regression model (QRM) Eq. (2) and its mean regression model (MRM) in Eq. (1) regarding the relationship between changes in the VIX and changes in VXEEM. The model in Eq. (2) includes 5 covariates and an intercept. For the QRM, for each of the 5 coefficients, 19 quantile regression coefficient estimates are estimated for each q in the range q={0.05,…,0.95}. The coefficient estimates for the MRM are reported in the 12th row of Table 2. The contemporaneous relation between ΔVIX and ΔVXEEM is captured by $\gamma_{(0)}^{(q)}$ as the coefficient sign is positive and significant across the conditional distribution of ΔVXEEM. Moreover, variations are illustrated in the contemporaneous relationship across the conditional distribution. For instance, the magnitude of the relationship at the lowest quantile (q=0.05) is 0.63 whereas at the highest one (q=0.95) is 0.78 (the median relationship is 0.65). In case we compare the interrelationship below and above the median quantile, it is apparent that the contemporaneous coefficient estimate below the median quantile is not varying; however, above the median quantile the contemporaneous relationship is far more pronounced as the difference estimates between the highest quantile (q=0.95) and the median (0.50) is about 13 basis points. This result is further confirmed by the quantile slope equality test (shown in the lowest panel of Table 2). Furthermore, when comparing the contemporaneous coefficient estimates of the QRM, we observe that the OLS estimate is somehow similar to the estimates of the median quantile, hence the OLS is not able of capturing volatility dependence at the upper tails. In fact, the OLS underestimates the link beyond the median quantile up to the highest quantile (q=0.95). Next, the lagged relationships between ΔVIX and ΔVXEEM are reported in column 5 and 6. The estimates are positive and significant at the 1st lag, yet the relationship becomes weaker and mostly insignificant at lag 2. The contemporaneous relationship at the upper-most quantile (q=0.95) is more than three times higher than of lag 1, a fact which suggests that the linkages between the fear index and the overall emerging market volatility are mostly of a contemporaneous nature rather than characterized by a lagged pattern.

The size of the changes in the fear index - irrespective of the contemporaneous directionality - is captured by $\delta^{(q)}$, i.e., the coefficient estimates for absolute changes in the VIX which are reported in column 4 of Table 2. The effect is statistically significant beyond the median quantile up to the upper-most quantile, however for the lower quantiles the effect is insignificant. If we compare this coefficient estimate vis-à-vis the estimate derived by the OLS (row 12), we have a clear evidence that the traditional method is unable to capture the size effect. Specifically, the coefficient value for absolute changes is small and statistically insignificant. Our results imply that besides directionality, the size of the VIX changes is very important in capturing emerging market volatilities.

Furthermore we investigate whether the relationship between ΔVIX and ΔVXEEM is asymmetric. This can be revealed by the values of [$\gamma_{(0)}^{(q)}+\delta^{(q)}$] and [$\gamma_{(0)}^{(q)}-\delta^{(q)}$], which depict the asymmetric effect of positive and negative impact of the fear index upon the emerging market index. The calculated values suggest that when the VIX increases by 100 basis points, the VXEEM will rise by 103 basis points for the q=0.95 (or 70 basis points using the OLS). On the other hand, when the VIX falls by 100 basis points, the VXEEM index will fall by 53 basis points at the *q*=0.95 (63 basis points for the OLS). Thus, for the extreme-tail (*q*=0.95) of the VXEEM distribution, the effect of the positive shock is about two times more pronounced than the effect of a negative shock in the VIX. Interestingly, when comparing the absolute difference between increased and decreased values at *q*=0.95 vs. the OLS, the absolute value at the upper-quantiles is about eight times higher than those produced by OLS. Clearly the asymmetry in the relationship between ΔVIX and ΔVXEEM is robustly captured by the quantile regression, in particular in the upper-most quantiles. The conventional OLS is unable to reflect the inherent asymmetry in the relationship between ΔVIX and ΔVXEEM. Across the quantiles of the volatility changes distribution, the asymmetry is temporally varying; it is weaker and insignificant below the median quantile i.e., in the lower-tail of the distribution, while it emerges strongly beyond the median quantile of the distribution.

4.2 Volatility relationship between the fear index and the Chinese market

Table 3 reports the quantile regression model estimates (QRM) of Eq. (2) and its mean regression model (MRM) of Eq. (1) for the changes in the VIX and the Chinese market volatility index (VXFXI). The contemporaneous relationship as shown by $\gamma_{(0)}^{(q)}$ is positive and significant across the distribution of ΔVXFXI. while the magnitude of the linkage at the lowest quantile (*q*=0.05) is 0.40 and at the highest is 0.64 (the median relationship is 0.40). The contemporaneous coefficient estimate below the median-quantile varies around 0.40 which is similar to the median coefficient, however above the median-quantile the dispersion in the relationship is significantly high, and when moving up across the distribution it tends to strengthen at about 24 basis points quantile difference scale. This result is confirmed by the quantile slope equality test reported in the low panel of Table 3. The OLS point estimate is about similar as the estimate of the median-quantile, implying that OLS cannot really capture the volatility relationship particularly at the upper-part of the conditional distribution.

Next, the lagged relationship is reported in columns 5 and 6. The estimates are positive and significant at the 1st lag and appear weaker or even insignificant at higher lags. The contemporaneous association between ΔVIX and ΔVXFXI at the upper-most quantile is about five times higher compared to the one at lag 1. The $\delta^{(q)}$ (size effect) estimates are reported in column 4, Table 3. The absolute impact of the VIX shocks is statistically significant, particularly above the median-quantile up to the upper-most quantile (*q*=0.95). The OLS estimate of the size is statistically insignificant and small in magnitude. The asymmetry in the relationship between ΔVIX and ΔVXFXI which can be reflected by the values of [$\gamma_{(0)}^{(q)}$+$\delta^{(q)}$] and [$\gamma_{(0)}^{(q)} - \delta^{(q)}$] show that an 100 basis points increase in the VIX leads to 94 basis points augmentation in the VXFXI at the *q*=0.95 (only 47 basis points for the OLS). When the VIX falls by 100 basis points, the drop in the VXFXI is 34 basis points (40 basis points for the OLS). At the extreme-tail (*q*=0.95) of the VXFXI conditional distribution, the effect of a positive shock in the VIX is about three times more pronounced than by a negative shock. Moreover, the absolute value at the *q*=0.95 is about eight times higher than that of the OLS estimate. Thus, the asymmetry is stronger in the upper-most tail of the distribution and OLS seriously underestimates the skewed relationship at the higher quantiles. Across quantiles, the asymmetry tends to be even more time-varying.

4.3 Dependencies between VIX and the Brazilian volatility index

In Table 4 we display the quantile regression model (QRM) and its mean regression model (MRM) for the changes in the VIX and changes and in the Brazilian volatility index (VXEWZ). The contemporaneous relationship captured by $\gamma_{(0)}^{(q)}$ is positive and statistically significant whilst it varies across the conditional distribution. The magnitude of the relationship at the lowest quantile is 0.41 whereas at the highest-quantile is 0.53. The dependence at the median-quantile is 0.42, and the variation below the median is very low. However, at the higher-quantiles of the distribution the relationship tends to vary widely compared to the other indices and to become stronger as the difference between the highest quantile and the median estimates reach about 11 basis points. We can confirm this finding by estimating the quantile slope equality test (low panel of Table 4). The OLS estimate seems about similar to the estimate of the median-quantile, implying the discrepancy of the OLS methodology particularly beyond the median quantile.

The lagged relationship between ΔVIX and ΔVXEWZ is reported in columns 5 to 6. The coefficients are positive and significant for the first lag and then turn insignificant. Specifically, the contemporaneous relationship at the upper-most quantile (*q*=0.95) is about three times higher than at the first lag, which suggests that the volatility linkages between the fear index and the Brazilian volatility are mostly contemporaneous in nature, even though only in this case we detect some lagged effect as well. The size effect i.e., $\delta^{(q)}$ as reported in column 4 of Table 4 (absolute effect) of the VIX shocks is statistically significant, particularly above the median quantile up to the upper-most quantile. The asymmetry revealed by [$\gamma_{(0)}^{(q)}$+$\delta^{(q)}$] and [$\gamma_{(0)}^{(q)} - \delta^{(q)}$] shows that 100 basis points increase in the VIX leads to 71 basis points increase in the VXEWZ at *q*=0.95 (or 46 basis points for the OLS), and a 100 basis points drop, leads to 35 basis points decline of the VXEWZ (or 41 basis points for the OLS) at *q*=0.95. If we compare the effects of positive/negative shocks of the VIX at extreme-tails vis-à-vis the VXEWZ, a positive shock is about twice as important as a negative one. Lastly, the absolute difference at *q*=0.95 is about seven times higher than the value generated by OLS, hence implying that the asymmetry is stronger in the upper-most tail of the conditional distribution. The observed asymmetry follows a time-varying pattern and appears enhanced in the upper part of the conditional distribution.

4.4 Time-varying asymmetries in the volatility dependence structure

We filter the marginals to account for second-moment effects. Accordingly, the dynamic time-varying asymmetric dependence structure can be robustly captured using multivariate copula analysis. Table 5 displays the results of pre-filtering utilizing an optimally selected GJR-GARCH (1,1) specification as corroborated by the diagnostics applied to the standardized residuals and standardized squared residuals. The dynamic time-varying asymmetric dependence has appealing features as it offers flexibility in modeling separately the marginals, which are invariant to monotonic transformations of the VIX, VXEEM, VXFXI, and VXEWZ. The TVP-copula provides information on both the mean and tail dependence between the VIX and VXEEM, VXFXI, VXEWZ.

Table 6 presents the results for time-varying copulas. The rotated Gumbel copula appears to provide the best description of the volatility dependence structure based on the maximum log-likelihood scores. In order to check for robustness, we also consider the return and tail dependence between VXEFA and VXEEM, VXFXI, VXEWZ. The time-varying rotated Gumbel copula seems to provide the best description compared to the time-varying normal copula and the time-varying SJC copula. The volatility dependence structure measurement is based on the maximum log-likelihood scores.

Figures 2, 3 and 4 display clearly that copula parameters change over time. Figure 2 depicts the dependence structure derived by a time-varying Normal copula; we observe that the variation for the pair VIX-VXEEM (VXEFA-VXEEM) lies from 0.68 to 0.81 (0.65-0.88), for VIX-VXFXI (VXEFA-VXFXI) from 0.25 to 0.81 (0.40-0.88), whilst for VIX-VXEWZ (VXEFA-VXFXI) within the interval 0.40-0.84 (0.45-0.90). Figure 3 illustrates the second-moment dependence captured by the rotated Gumbel copula. The dependence parameter ranges from 1.95 to 2.50 (1.40-2.59) for the VIX-VXEEM pair (VXEFA-

VXEEM), from 1.20 to 2.10 (1.05-2.12) for the VIX-VXFXI (VXEFA-VXFXI), while lastly from 1.25 to 2.50 (1.18-2.10) for the VIX-VXEWZ (VXEFA-VXEWZ) pairwise.

Moreover, Figure 4 displays the left and the right tail time-varying dependence for all three pairs based on the TVP-SJC copula. Overall, the dependence for VIX-VXEEM, VIX-VXFXI and VIX-VXEWZ in the left-tail (lower tail) is higher. The reverse result is weakly observed for the VIX-VXFXI and VIX-VXEWZ cases, whilst the upper-tail dependence for VIX-VXEEM is found to be insignificant during the investigated sample. All in all, the dependence for the pairs VXEFA-VXEEM, VXEFA-VXFXI and VXEFA-VXEWZ in the left-tail (lower tail) and right-tail (upper tail) is significant during the examined period.

To summarize, firstly we find overwhelming evidence that all three volatility indices show a high degree of second-moment tail dependence against the VIX and VXEFA index over the entire period. Secondly, this structure is the strongest and most persistent for the pair VIX-VXEEM followed by VIX-VXEWZ and VIX-VXFXI. Finally during tranquil periods, dependence is lower on average, however it is significantly increased in crisis eras.

5. Robustness Analysis

To check the robustness of our results, we changed our independent variable in Eq.(1) and (2) by utilizing the developed market volatility index (VXEFA) instead of the VIX index, and the VXEFA which depicts the volatility of 24 developed stock markets, excluding the US. Both specifications namely MRM (Eq.1) and QRM (Eq.2) are re-estimated. The results are reported in Table 7. In panel A, we show the results for the volatility linkages across the distribution of the VXEEM. The comparison against the findings of Table 2, reveals that the R-square values for all of quantiles including OLS are about 6% lower as well as the coefficients upon the contemporaneous and lagged coefficients are lower vis-à-vis Table 2. In panel B, we display the results for volatility linkages across the distribution of the VXFXI. In this case, the R-square values for all of quantiles are about 2%-3% lower than those of Table

3. Similarly, the contemporaneous and lagged coefficients decline in value. Next, in Panel C the results for the VXEWZ are incorporated. It is obvious that the R-square values for all of quantiles are about 4%-5% lower the ones reported in Table 4 and the coefficients once more are lower too. Overall, the causal links between the emerging volatilities and the fear index (VIX) are stronger and more robust than the ones produced for the overall developed market index (VXEFA) as documented further in Table 7.

Finally, Table 8 reports the linear and non-linear Granger causalities between the fear index and emerging market volatility indices. As a robustness check, we replaced the fear index with the overall developed markets index (VXEFA). Panel 1 of Table 8 shows linear Granger causality results. While it appears that VIX significantly granger causes all three emerging market volatility indices, yet a bi-directional causality emerges in case of VIX and Chinese volatility index. If we substitute the VIX with VXEFA, we observe causality running now from the overall developed market index (VXEFA) to the emerging market index and the Brazilian volatility index. However, VXEFA does not Granger causes Chinese volatility index (VXFXI) in this case. Overall for linear causalities we conclude that the VIX plays a more dominant role in co-movements compared to VXEFA. From the non-linear Granger causality testing conducted, as depicted in Panel 2 (Table 8), we realize that the fear index causes the emerging volatility index. Nevertheless, if we replace VIX with VXEFA, the non-linear links vanish with respect to the emerging market volatility index.

6. CONCLUSIONS

In this work, we investigate the relationship between changes in the fear index (VIX) and the emerging markets of China and Brazil as well as of an overall emerging stock market volatility measure, across their conditional distributions. We also study the inherent asymmetries observed with respect to positive and negative shocks in the fear index. We find a strong contemporaneous relationship between changes in the VIX and changes in the emerging market volatility indices. The links tend to be stronger in the upper tails of the conditional distribution of the volatility changes. In particular, the contemporaneous effects are pronounced at the extreme quantiles i.e., over the 95% quantile. When we compare the contemporaneous vis-à-vis the lagged relationships across distributions, we find that on average the contemporaneous ones are three times higher. Moreover, we were able to reveal significant asymmetries: at the 95% quantile the effect of positive changes in the VIX is almost twice as high as the one by negative changes for all emerging markets, which is not detected by OLS. Finally, when we compare the asymmetric responses of the volatility indices to positive shocks versus negative shocks in the VIX, the absolute difference is highest for the Chinese stock market. This fact implies that Chinese investors are more responsive to changes in the VIX compared to market agents in the other emerging markets.

These statistically significant asymmetric contemporaneous relationships between changes in the VIX and emerging markets lead directly to less diversification opportunities. Yet, novel strategies can be devised to manage and diversify risks arising from equity positions in the emerging stock markets. For instance, as proposed in Alexander *et al.* (2016) including volatility derivatives products (e.g., call options or volatility futures) for VXFXI, VXEWZ, and VXEEM might enhance risk mitigation, or incorporating ETNs could also offset the losses on equity positions. An exhaustive robustness analysis was also performed with respect to other volatility measures.

References

Äijö, J., 2008. Implied volatility term structure linkages between VDAX, VSMI and VSTOXX volatility indices. *Global Finance Journal* 18(3), 290-302.

Alexander, C., Korovilas, D., Kapraun, D., 2016. Diversification with volatility products. *Journal of International Money and Finance* 65(July), 213-235.

Badshah, I., 2013. Quantile regression analysis of the asymmetric return-volatility relation. *Journal of Futures Markets* 33(3), 235-265.

Badshah, I., 2016. Volatility spillover from the fear index to developed and emerging markets, forthcoming in *Emerging Markets Finance and Trade*.

Barunik, J., Kocenda, E., Vacha, L., 2016. Asymetric connectedness on the U.S. stock market: Bad and good volatility spillovers. *Journal of Financial Markets* 27, 55-78.

Baur, D., Schulze, N., 2005. Coexceedances in financial markets--a quantile regression analysis of contagion. Emerging Markets Review 6 (1), 21-43.

Bekaert, G., Harvey, C., 2014. Emerging equity markets in a globalizing world. *Columbia Business School Working Paper*, New York.

Bekaert, G., Harvey, C., Lundblad, C., Siegel, S., 2011. What segments equity markets? *Review of Financial Studies* 24 (12), 3841-3890.

Bekaert, G., Hoerova, M., Duca Lo, M., 2013. Risk, uncertainity, and monetary policy. *Journal of Monetary Economics* 60(7), 771-788.

Blair, B., Poon, S., Taylor, S., 2001. Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high-frequency index returns. *Journal of Econometrics* 105(1), 5-26.

Bloom, N., 2014. Fluctuations in uncertainty. *Journal of Economic Perspectives* 28(2), 153-176.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. *Review of Financial Studies* 22(11), 4463-4492.

Cappiello, L., Engle, R., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics* 4(4), 537-572.

Diebold, F. X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal* 119(534), 158-171.

Diebold, F. X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting 28*(1), 57-66.

Diebold, F. X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics 182*, 119-134.

Diks, C. and Panchenko, V. 2005. A note on the Hiemstra-Jones test for Granger noncausality. *Studies in Nonlinear Dynamics and Econometrics*, 9 art. 4.

Diks, C. and Panchenko, V. 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control*, 30, 1647-1669.

Hiemstra, C. and Jones, J. D. 1994. Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. *Journal of Finance*, 49, 1639-1664.

Glosten, L., Jagannathan, R., Runkle, D., 1993. On the relation between expected excess return on stocks. *Journal of Finance* 48(5), 1779-1801.

Jiang, G., Konstantinidi, E., and Skiadopoulos, G., 2012. Volatility spillovers and the effect of news announcements. *Journal of Banking and Finance* 36 (8), 2260-2273.

Kenourgios, D., 2014. On financial contagion and implied market volatility. International *Review of Financial Analysis* 34, 21-30.

Koenker, R., Bassett, G., 1978. Regression quantiles. *Econometrica* 46, 33-50.

Low, C., 2004. The fear and exuberance from implied volatility of S&P 100 index options. *Journal of Business* 77, 527-546.

Nikkinen, J., Sahlström, P., 2004. International transmission of uncertainty implicit in stock index option prices. *Global Finance Journal* 15 (1), 1-15.

Nikkinen, J., Sahlström, P., Vähämaa, S., 2006. Implied volatility linkages among major european currencies. *Journal of International Financial Markets, Institutions, and Money* 16(2), 87-103.

Patton, A., 2006. Modelling asymmetric exchange rate dependence. *International Economic Review* 47 (2), 527-556.

Peng, W., Ng, W., 2012. Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. *Annals of Finance* 8 (1), 49-74.

Poon, S., Granger, C., 2003. Forecasting volatility in financial markets: A review. *Journal of Economic Literature* 41(2), 478-539.

Segal, G., Shaliastovich, I., Yaron, A., 2015. Good and bad uncertainty: macroeconomic and financial market implications. *Journal of Financial Economics* 117 (2), 369–397

Skiadopoulos, G., 2004. The Greek implied volatility index: Construction and properties. *Applied Financial Economics* 14(16), 1187-1196.

Whaley, R., 2000. The investor fear gauge. *Journal of Portfolio Management* 26(3), 12-17.

Whaley, R., 2009. Understanding the VIX. *Journal of Portfolio Management* 35(3), 98-105.

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TABLE 1: DESCRIPTIVE STATISTICS

Panel A: Volatility levels				
	VIX	VXEEM	VXFXI	VXEWZ
Mean	17.41496	24.86070	27.44063	31.83350
Median	15.64000	23.28000	25.63000	29.44000
Maximum	48.00000	64.10000	63.42000	72.83000
Minimum	10.32000	13.71000	16.93000	16.67000
Std.Dev.	5.892830	7.715476	7.243760	9.197550
Skewness	2.071987	1.834481	1.690898	1.137013
Kurtosis	7.624936	7.139310	6.320473	4.361235
ρ_1	0.960***	0.966***	0.967***	0.976***
ADF	-3.821***	-3.023**	-4.229***	-3.504***
No. Obs	1263	1263	1263	1263

Panel B: Volatility changes				
	ΔVIX	ΔVXEEM	ΔVXFXI	ΔVXEWZ
Mean	-0.000067	0.000055	0.000149	0.000346
Median	-0.001932	-0.001950	-0.002885	-0.000754
Maximum	0.405465	0.504862	0.365767	0.312019
Minimum	-0.314140	-0.298065	-0.185139	-0.619580
Std.Dev.	0.074400	0.062080	0.050744	0.050265
Skewness	0.744525	0.985119	1.229998	-0.778951
Kurtosis	6.268968	8.601176	8.532195	23.76351
ρ_1	-0.073***	-0.023	0.015	-0.001
ADF	-38.160***	-23.166***	-34.853***	-35.490***
No. Obs	1263	1263	1263	1263

Notes: We report descriptive statistics for the log-changes of the VIX, VXEEM, VXFXI and VXEWZ at daily frequencies. The autocorrelation coefficient ρ and the Augmented Dickey-Fuller (ADF) (intercept is included) test values are reported. ***, **, and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

TABLE 2: VOLATILITY LINKAGES ACROSS DISTRIBUTIONS: RESPONSE VARIABLE ΔVXEEM

q	$Intercept$	ΔVIX_t	$\lvert\Delta VIX_t\rvert$	ΔVIX_{t-1}	ΔVIX_{t-2}	$\Delta VXEEM_{t-1}$	R^2
0.05	-0.048***	0.635***	-0.107	0.133*	0.113***	-0.126	36.7%
	(-10.19)	(12.45)	(-1.37)	(1.87)	(2.80)	(-1.19)	
0.10	-0.037***	0.615***	-0.089**	0.164***	0.093***	-0.138**	37.1%
	(-14.06)	(21.98)	(-2.19)	(3.47)	(3.21)	(-2.17)	
0.15	-0.030***	0.619***	-0.061	0.159***	0.076***	-0.146**	37.3%
	(-13.17)	(21.74)	(-1.59)	(3.66)	(3.34)	(-2.46)	
0.20	-0.026***	0.621***	-0.011	0.163***	0.050**	-0.160***	37.7%
	(-11.71)	(25.21)	(-0.31)	(3.73)	(2.37)	(-2.67)	
0.25	-0.020***	0.625***	-0.003	0.146***	0.029	-0.122**	37.8%
	(-10.25)	(30.66)	(-0.12)	(3.54)	(1.58)	(-2.18)	
Median	-0.001***	0.650***	0.0142	0.139***	0.031	-0.114***	40.0%
	(-0.963)	(31.65)	(0.62)	(4.21)	(1.60)	(-3.21)	
0.75	0.0150***	0.670***	0.092***	0.225***	0.020	-0.213***	43.0%
	(8.19)	(35.84)	(3.60)	(7.30)	(1.17)	(-5.62)	
0.80	0.020***	0.684***	0.095***	0.225***	0.011	-0.198***	43.6%
	(9.05)	(25.14)	(2.76)	(6.80)	(0.49)	(-4.77)	
0.85	0.024***	0.724***	0.165***	0.223***	0.025	-0.193***	44.2%
	(10.00)	(22.98)	(4.13)	(6.08)	(1.16)	(-4.37)	
0.90	0.032***	0.720***	0.184***	0.265***	0.038	-0.226***	44.9%
	(9.69)	(21.32)	(3.83)	(5.77)	(1.25)	(-4.40)	
0.95	0.046***	0.780***	0.250***	0.227***	0.043	-0.226***	46.7%
	(9.77)	(19.88)	(4.32)	(3.38)	(1.12)	(-2.81)	
OLS	-0.001	0.665***	0.031	0.202***	0.040**	-0.191***	64.88%
	(-1.13)	(32.00)	(1.29)	(6.94)	(2.23)	(-4.97)	

Quantile Slope Equality Test Results: Only significant results of volatility spillover are reported.

					0.2-0.4*		
			0.4-0.6***				
				0.6-0.8***			
		0.8-0.9***	0.8-0.9***				

Notes: The MM QM specification 1 and 2 respectively, are estimated for the volatility spillovers between changes in the VXEEM and VIX. In the context of QM, the standard errors are obtained from a bootstrap method; therefore, robust *t*-statistics (in parentheses) are computed for each of the quantile estimates. The MM specification 1 is estimated via the Newey-West (Newey and West, 1987) correction test for heteroscedasticity and autocorrelation. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

TABLE 3: VOLATILITY LINKAGES ACROSS DISTRIBUTIONS: RESPONSE VARIABLE ΔVXFXI

q	$Intercept$	ΔVIX_t	$\lvert\Delta VIX_t\rvert$	ΔVIX_{t-1}	ΔVIX_{t-2}	$\Delta VXFXI_{t-1}$	R^2
0.05	-0.045***	0.396***	-0.216***	0.107***	0.053*	-0.148**	26.8%
	(-13.85)	(9.72)	(-3.52)	(2.73)	(1.73)	(-2.51)	
0.10	-0.033***	0.357***	-0.180***	0.142***	0.028	-0.155***	22.7%
	(-15.63)	(12.69)	(-5.55)	(4.79)	(1.09)	(-3.47)	
0.15	-0.027***	0.401***	-0.130***	0.136***	0.037	-0.136***	21.2%
	(-15.50)	(13.71)	(-4.10)	(5.34)	(1.56)	(-3.28)	
0.20	-0.022***	0.360***	-0.089***	0.123***	0.028	-0.113***	20.7%
	(-13.25)	(16.76)	(-3.20)	(5.14)	(1.26)	(-2.78)	
0.25	-0.018***	0.364***	-0.082***	0.132***	0.036*	-0.136***	20.8%
	(-10.18)	(17.93)	(-2.89)	(5.61)	(1.67)	(-3.46)	
Median	-0.002***	0.400***	0.019	0.113***	0.050**	-0.124***	22.1%
	(-1.44)	(22.62)	(0.86)	(4.43)	(2.34)	(-2.63)	
0.75	0.012***	0.455***	0.127***	0.122***	0.071***	-0.121***	26.2%
	(6.35)	(16.45)	(3.55)	(4.47)	(3.46)	(-3.26)	
0.80	0.017***	0.480***	0.153***	0.140***	0.074***	-0.127***	27.4%
	(7.71)	(16.95)	(3.84)	(4.76)	(3.37)	(-2.78)	
0.85	0.023***	0.499***	0.182***	0.131***	0.060***	-0.117**	28.55
	(10.18)	(16.51)	(4.47)	(3.73)	(2.79)	(-2.00)	
0.90	0.031***	0.530***	0.225***	0.122***	0.056**	-0.074	30.3%
	(9.90)	(12.15)	(4.16)	(2.74)	(2.04)	(-1.13)	
0.95	0.046***	0.636***	0.299***	0.136**	0.015	-0.004	34.1%
	(10.44)	(12.02)	(3.84)	(2.54)	(0.42)	(-0.05)	
OLS	-0.001	0.436***	0.038	0.117***	0.053**	-0.101**	42.6%
	(-1.34)	(14.80)	(1.59)	(4.40)	(2.47)	(-2.43)	

Quantile Slope Equality Test Results: Only significant results of volatility spillover are reported.

		0.2-0.4*	0.2-0.4***				
			0.4-0.5**				
		0.6-0.9***	0.6-0.9***				

Notes: The MM QM specification 1 and 2 respectively are estimated for the volatility spillovers between changes in the VXFXI and VIX. In the context of QM, the standard errors are obtained from a bootstrap method; therefore, robust *t*-statistics (in parentheses) are computed for each of the quantile estimates. The MM specification 1 is estimated via the Newey-West (Newey and West, 1987) correction test for heteroscedasticity and autocorrelation. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

TABLE 4: VOLATILITY LINKAGES ACROSS DISTRIBUTIONS: RESPONSE VARIABLE ΔVXEWZ

q	$Intercept$	ΔVIX_t	$\lvert\Delta VIX_t\rvert$	ΔVIX_{t-1}	ΔVIX_{t-2}	$\Delta VXEWZ_{t-1}$	R^2
0.05	-0.040***	0.406***	-0.233***	0.116***	0.051**	-0.111	24.5%
	(-11.36)	(11.38)	(-4.68)	(2.60)	(2.06)	(-1.53)	
0.10	-0.031***	0.409***	-0.130**	0.126***	0.041	-0.089**	24.5%
	(-9.19)	(11.47)	(-2.16)	(3.43)	(1.53)	(-2.03)	
0.15	-0.023***	0.413***	-0.134***	0.102***	0.022	-0.040	24.3%
	(-10.72)	(19.76)	(-3.59)	(3.76)	(1.12)	(-1.10)	
0.20	-0.019***	0.412***	-0.114***	0.092***	0.026	-0.034	24.1%
	(-10.20)	(21.48)	(-3.52)	(3.63)	(1.39)	(-0.88)	
0.25	-0.016***	0.403***	-0.071**	0.091***	0.025	-0.059	23.8%
	(-8.63)	(20.40)	(-1.97)	(3.91)	(1.42)	(-1.41)	
Median	-0.001	0.415***	0.022	0.073***	0.034**	-0.066**	23.4%
	(-1.03)	(22.18)	(1.00)	(3.60)	(2.24)	(-2.13)	
0.75	0.012***	0.453***	0.178***	0.056**	0.034**	-0.029	27.9%
	(6.92)	(21.26)	(6.26)	(2.24)	(2.12)	(-1.08)	
0.80	0.018***	0.459***	0.172***	0.050**	0.034**	-0.025	29.4%
	(9.44)	(23.83)	(6.36)	(2.16)	(2.03)	(-1.00)	
0.85	0.025***	0.483***	0.164***	0.067***	0.019	-0.037	31.2%
	(14.17)	(22.26)	(5.58)	(2.80)	(1.16)	(-1.16)	
0.90	0.032***	0.515***	0.163***	0.052*	0.013	-0.020	33.2%
	(19.11)	(25.58)	(6.49)	(1.92)	(0.68)	(-0.56)	
0.95	0.047***	0.528***	0.178***	0.074*	0.018	-0.066	36.5%
	(14.36)	(10.52)	(3.23)	(1.74)	(0.39)	(-1.09)	
OLS	-0.000	0.431***	0.025	0.092***	0.051**	-0.083***	41.6%
	(-0.56)	(16.10)	(0.88)	(3.96)	(2.33)	(-2.66)	

Quantile Slope Equality Test Results: Only significant results of volatility spillover are reported.							
		0.2-0.4*	0.2-0.4***				
			0.4-0.5**				
		0.6-0.9***	0.6-0.9***				

Notes: The MM QM specification 1 and 2 respectively are estimated for the volatility spillovers between changes in the VXEWZ and VIX. In the context of QM, the standard errors are obtained from a bootstrap method; therefore, robust *t*-statistics (in parentheses) are computed for each of the quantile estimates. The MM specification 1 is estimated via the Newey-West (Newey and West, 1987) correction test for heteroscedasticity and autocorrelation. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

TABLE 5: SPECIFICATION TESTS FOR FILTERED SERIES

	VIX	VXEEM	VXFXI	VXEWZ
Skewness	0.91	0.98	1.22	-0.77
Kurtosis	2.84	8.59	8.52	23.74
AIC	-2.53	-2.90	-3.42	-3.47
SIC	-2.51	-2.87	-3.39	-3.44
Q(10)	14.77	15.39	13.38	8.70
$Q^2(10)$	14.73	6.40	4.27	11.55
ARCH(10)	1.41	1.03	0.50	1.07
J-B	604.39***	482.64***	726.73***	1758.30***

Notes: The GJR-GARCH (1,1) 2nd moment filter is applied on the investigated series. ** and *** indicate the rejection of the null at the 5% and 1% levels, respectively. *JB* stands for the Jarque-Bera test, Q(10) and $Q^2(10)$ for the Ljung-Box autocorrelation test for 10 lags. ARCH represents the Engle (1982) test for conditional heteroscedasticity.

TABLE 6: TIME-VARYING COPULA ESTIMATES

	VIX			VXEFA *(Robustness checking)*		
	VXEEM	**VXFXI**	**VXEWZ**	**VXEEM**	**VXFXI**	**VXEWZ**
			TIME-VARYING NORMAL COPULA			
Ψ_0	-0.362 (0.9261)	-0.133 (0.060)	-0.405 (0.032)	4.621 (0.196)	-2.585 (0.168)	2.972 (0.188)
Ψ_1	-0.050 (0.035)	0.105 (0.028)	0.078 (0.008)	0.439 (0.078)	0.597 (0.079)	0.603 (0.107)
Ψ_2	3.241 (1.133)	2.480 (0.126)	2.960 (0.058)	-4.120 (0.162)	-2.649 (0.139)	-3.059 (0.103)
LogLik.	622.58	331.24	372.12	499.64	293.59	318.00
			TIME-VARYING ROTATED GUMBEL COPULA			
Ψ_0	2.021 (0.423)	0.297 (0.303)	0.210 (0.071)	2.354 (0.018)	1.696 (0.410)	1.701 (0.325)
Ψ_1	-0.314 (0.186)	0.382 (0.137)	0.424 (0.025)	-0.435 (0.018)	-0.258 (0.186)	-0.278 (0.161)
Ψ_2	-1.449 (0.708)	-0.615 (0.388)	-0.489 (0.145)	-2.774 (0.582)	-2.394 (0.646)	-2.065 (0.456)
LogLik.	**567.51**	**302.40**	**347.56**	**477.59**	**282.66**	**300.33**
			TIME-VARYING SJC COPULA			
Ψ_0	2.266 (0.090)	-1.989 (0.051)	-2.004 (0.016)	3.609 (1.091)	3.732 (1.750)	2.314 (0.967)
Ψ_1	-0.030 (0.037)	-0.271 (0.105)	-0.234 (0.077)	-6.588 (2.139)	-12.829 (8.601)	-6.639 (1.990)
Ψ_2	-2.505 (0.045)	4.074 (1.604)	4.088 (0.035)	-3.316 (1.381)	-3.308 (0.759)	-2.315 (1.413)
Ψ_3	2.106 (0.142)	1.604 (0.933)	-0.376 (0.236)	2.165 (1.621)	1.307 (3.102)	1.023 (0.637)
Ψ_4	-5.046 (0.231)	-7.113 (2.863)	-3.301 (0.588)	-6.881 (4.649)	-5.518 (6.919)	-5.295 (1.700)
Ψ_5	-2.220 (0.133)	-2.235 (1.625)	1.425 (0.343)	-2.560 (2.087)	-2.277 (4.961)	-1.568 (1.220)
LogLik.	619.97	355.16	399.12	531.85	319.11	334.79

Notes: The maximum likelihood estimates for the different copula models are reported. Standard error values are presented in parentheses. The sample period spans March 16, 2011 - 16, 2016. VIX is computed from the bid and ask prices of the cross-section of S&P 500 options whilst the other three volatility indices, namely VXEEM (for emerging stock markets), VXFXI (Chinese market), and VXEWZ (Brazilian stock market) are estimated similarly. Moreover, VXEFA represents the developed market volatility index.

TABLE 7: VOLATILITY LINKAGES ACROSS DISTRIBUTIONS (ROBUSTNESS CHECK)

Panel A: Volatility linkages across distributions: response variable ΔVXEEM

q	$Intercept$	$\Delta VXEFA_t$	$\lvert\Delta VXEFA_t\rvert$	$\Delta VXEFA_{t-1}$	$\Delta VXEFA_{t-2}$	$\Delta VXEEM_{t-1}$	R^2
0.05	-0.043***	0.561***	-0.359***	0.130*	0.060*	-0.157**	30.00%
	(-11.07)	(8.45)	(-4.94)	(1.78)	(1.73)	(-2.10)	
0.10	-0.032***	0.559***	-0.217***	0.160***	0.023	-0.205***	31.00%
	(-13.63)	(15.35)	(-4.65)	(3.70)	(0.89)	(-3.83)	
0.15	-0.028***	0.583***	-0.162***	0.197***	0.024	-0.230***	31.02%
	(-10.09)	(14.83)	(-2.95)	(4.32)	(0.89)	(-4.21)	
Median	-0.004***	0.679***	0.084**	0.188***	0.037***	-0.189***	34.38%
	(-2.62)	(32.26)	(2.44)	(5.28)	(2.89)	(-4.66)	
0.85	0.022***	0.674***	0.279***	0.167***	-0.003	-0.160***	40.68%
	(7.17)	(17.81)	(5.35)	(4.05)	(-0.11)	(-3.70)	
0.90	0.029***	0.715***	0.334***	0.186***	-0.003	-0.192***	42.25%
	(8.84)	(18.56)	(5.77)	(4.19)	(-0.10)	(-3.67)	
0.95	0.043***	0.678***	0.374***	0.208***	0.020	-0.212***	45.30%
	(12.05)	(16.28)	(6.40)	(4.16)	(0.43)	(-3.40)	
OLS	-0.003**	0.650***	0.070**	0.199***	0.042**	-0.221***	57.28%
	(-2.16)	(17.28)	(2.40)	(6.98)	(2.25)	(-6.98)	

Panel B: Volatility linkages across distributions: response variable ΔVXFXI

q	$Intercept$	$\Delta VXEFA_t$	$\lvert\Delta VXEFA_t\rvert$	$\Delta VXEFA_{t-1}$	$\Delta VXEFA_{t-2}$	$\Delta VXFXI_{t-1}$	R^2
0.05	-0.042***	0.369***	-0.323***	0.121***	0.045**	-0.165***	24.69%
	(-12.26)	(8.65)	(-5.99)	(3.62)	(1.97)	(-2.89)	
0.10	-0.030***	0.364***	-0.232***	0.137***	0.045**	-0.163***	20.69%
	(-10.94)	(10.31)	(-4.93)	(3.69)	(2.39)	(-2.92)	
0.15	-0.024***	0.370***	-0.194***	0.116***	0.038**	-0.159***	19.90%
	(-10.85)	(13.93)	(-5.46)	(4.40)	(1.98)	(-4.06)	
Median	-0.003**	0.432***	0.046*	0.130***	0.035**	-0.139***	20.58%
	(-2.44)	(25.37)	(1.79)	(6.66)	(2.26)	(-4.59)	
0.85	0.019***	0.484***	0.277***	0.131***	0.041	-0.107**	26.92%
	(8.23)	(17.47)	(6.68)	(3.60)	(1.39)	(-1.98)	
0.90	0.026***	0.529***	0.322***	0.125**	0.052	-0.105	28.38%
	(7.44)	(16.22)	(6.06)	(2.47)	(1.09)	(-1.31)	
0.95	0.046***	0.555***	0.340***	0.127	0.047	-0.020	30.94%
	(8.45)	(7.86)	(4.11)	(1.49)	(0.70)	(-0.15)	
OLS	-0.002*	0.434***	0.062**	0.119***	0.052***	-0.113***	39.00%
	(-1.83)	(12.10)	(2.17)	(4.63)	(2.61)	(-2.91)	

Panel B: Volatility linkages across distributions: response variable ΔVXEWZ

q	$Intercept$	$\Delta VXEFA_t$	$\lvert\Delta VXEFA_t\rvert$	$\Delta VXEFA_{t-1}$	$\Delta VXEFA_{t-2}$	$\Delta VXEWZ_{t-1}$	R^2
0.05	-0.042***	0.386***	-0.234***	0.129**	0.061	-0.136	19.87%
	(-11.10)	(8.44)	(-3.66)	(2.49)	(1.29)	(-1.62)	
0.10	-0.030***	0.404***	-0.179***	0.123***	0.052**	-0.112***	21.19%
	(-15.55)	(19.13)	(-5.32)	(5.40)	(2.07)	(-5.44)	
0.15	-0.023***	0.367***	-0.159***	0.115***	0.047**	-0.101***	20.49%
	(-11.35)	(16.24)	(-4.98)	(4.25)	(2.03)	(-2.74)	
Median	-0.001	0.409***	0.025	0.078***	0.018	-0.043	20.79%
	(-1.02)	(20.24)	(1.07)	(4.58)	(1.32)	(-1.61)	
0.85	0.024	0.482***	0.205***	0.108***	0.007	-0.115***	27.52%
	(9.82)	(15.52)	(4.39)	(3.32)	(0.23)	(-2.97)	
0.90	0.031***	0.506***	0.239***	0.118***	-0.006	-0.126***	29.65%
	(13.00)	(17.61)	(6.01)	(4.16)	(-0.28)	(-3.48)	
0.95	0.043***	0.537***	0.308***	0.135***	-0.013	-0.162**	32.82%
	(11.06)	(11.51)	(5.10)	(2.93)	(-0.27)	(-2.00)	
OLS	-000	0.415***	0.011	0.128***	0.040**	-0.137***	30.00%
	(-0.02)	(13.37)	(0.34)	(6.71)	(1.98)	(-4.95)	

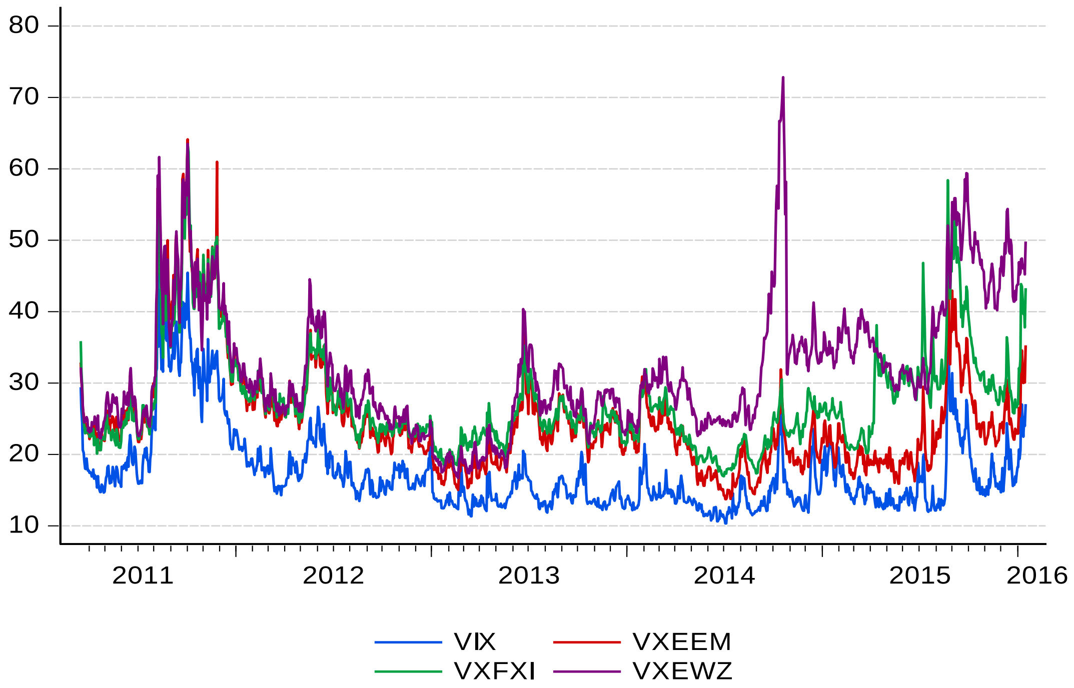
Notes: The MM QM specifications 1 and 2 are utilized respectively. These are estimated for the volatility spillovers between changes in the pairs i.e., VXEEM and VXEFA, VXFXI and VXEFA, VXEWZ and VXEFA. In the context of QM, the standard errors are obtained from a bootstrap method. Therefore, robust *t*-statistics (in parentheses) are computed for each of the quantile estimates. The MM specification 1 is estimated via the Newey-West (Newey and West, 1987) correction test for heteroscedasticity and autocorrelation. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

TABLE 8. LINEAR AND NON-LINEAR GRANGER CAUSALITY TEST (ROBUSTNESS CHECKING)

A-Series	VXEEM		VXFXI		VXEWZ	
DIRECTION	A→B	B→A	A→B	B→A	A→B	B→A
B-Series						
			LINEAR CAUSALITY			
VIX	0.32	7.35***	3.18**	5.35***	1.20	3.04***
VXEFA	1.01	19.14***	8.64***	1.69	2.86**	12.31***
			NON-LINEAR CAUSALITY			
VIX	0.01	3.16***	1.27*	0.087	0.92	1.21
VXEFA	1.09	0.18	2.48***	0.81	1.98**	0.06

Notes: *A*→*B* symbolizes that variable *A* does not cause variable *B* and *B*→ *A* that variable *B* does not cause variable A. [*], [**] and [***] denotes significance at the 1%, 5% and 10% statistical level of significance respectively. The number of lags used for the non-linear causality test are $\ell_c=\ell_s=1$. The non-linear causality was investigated based upon the nonlinear causality approach developed by Diks and Panchenko (2005, 2006), namely and fundamentally coinciding with the Hiemstra and Jones (1994) method.

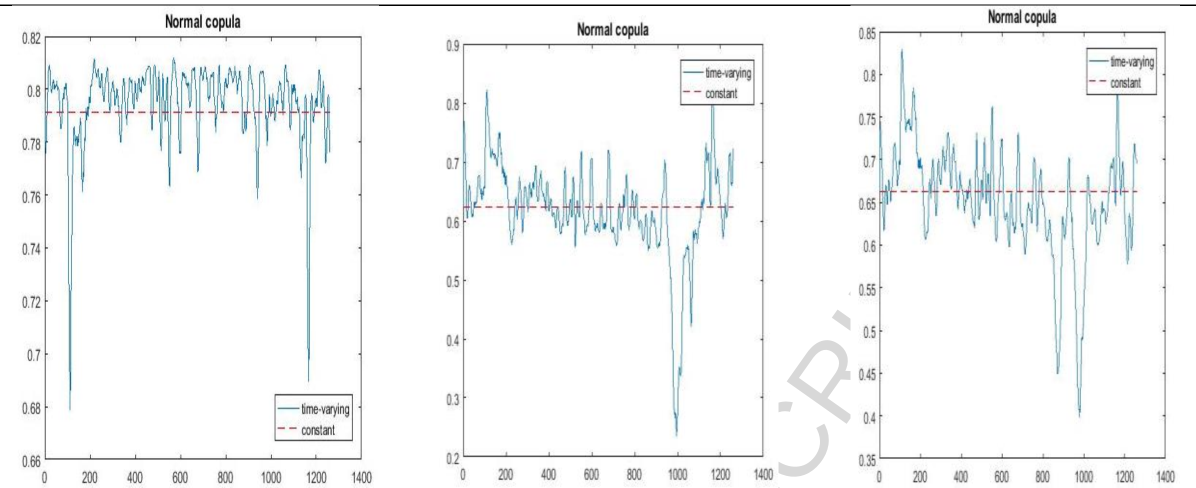
FIGURE 1: VOLATILITY INDICES



Notes: Time series plot of the VIX, VXEEM, VXFXI and VXEWZ from March 16, 2011 to January 16, 2016.

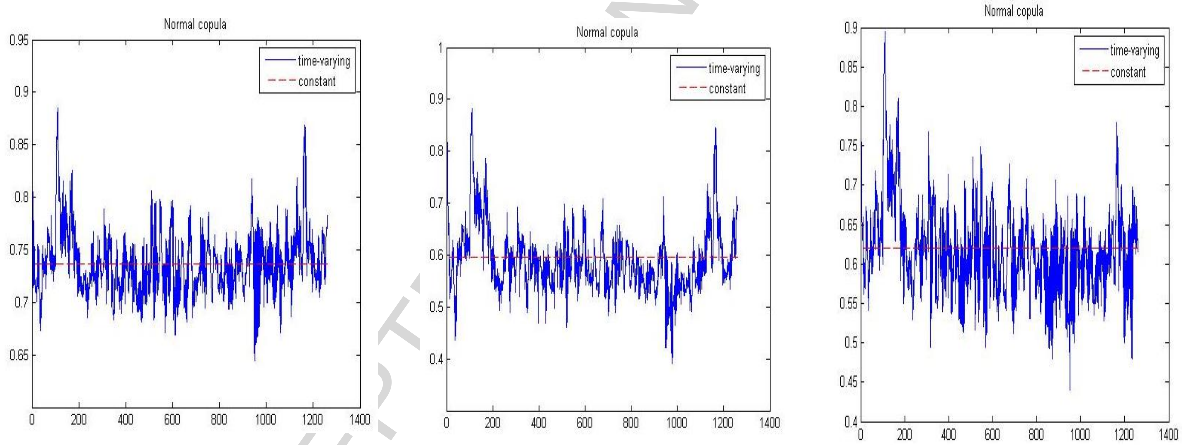
FIGURE 2: TVP-NORMAL COPULA DEPENDENCE MEASUREMENT

VIX-VXEEM **VIX-VXFXI** **VIX-VXEWZ**



ROBUSTNESS CHECK

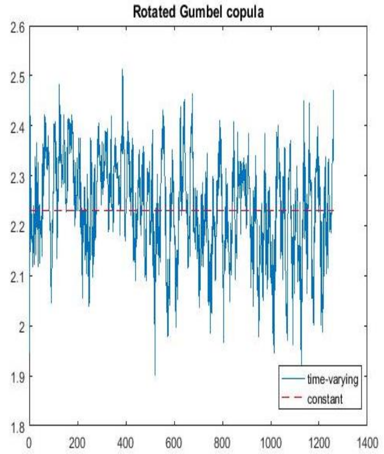
VXEFA-VXEEM **VXEFA-VXFXI** **VXEFA-VXEWZ**

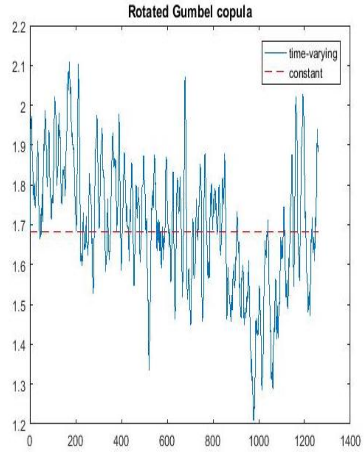


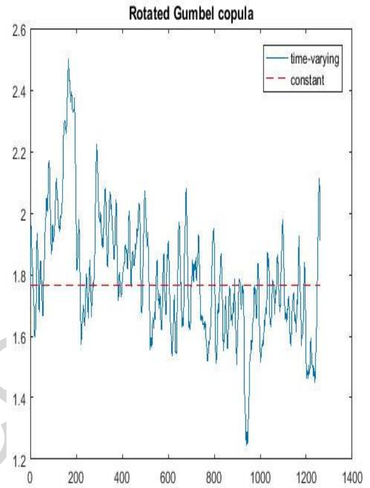
Notes: In the *X*-axis the time period is divided into 200, 400, 600, 800, 1000, 1200 up to 1264 daily obs. corresponding to the following dates: 2011-M_{12}-D_{20}, 2012-M_{09}-D_{25}, 2013-M_{07}-D_{02}, 2014-M_{04}-D_{08}, 2015-M_{01}-D_{13}, 2015-M_{10}-D_{20}- 2016-M_{01}-D_{16} respectively. The sample period spans March 16, 2011 to January 16, 2016.

FIGURE 3: TVP-ROTATED GUMBEL COPULA DEPENDENCE MEASUREMENT

VIX-VXEEM	VIX-VXFXI	VIX-VXEWZ

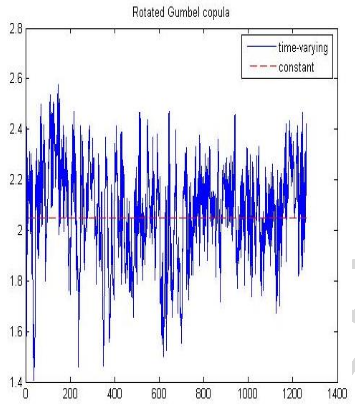


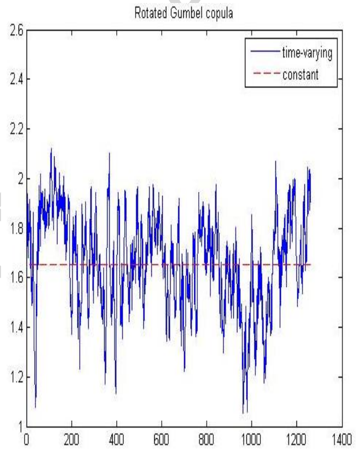


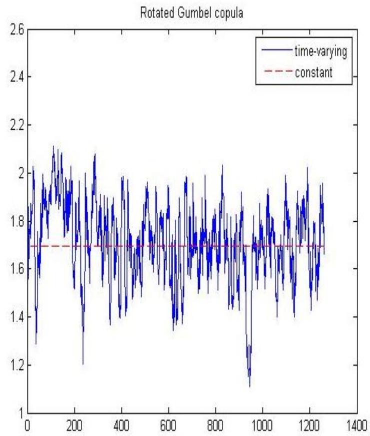


ROBUSTNESS CHECK

VXEFA -VXEEM	VXEFA -VXFXI	VXEFA -VXEWZ

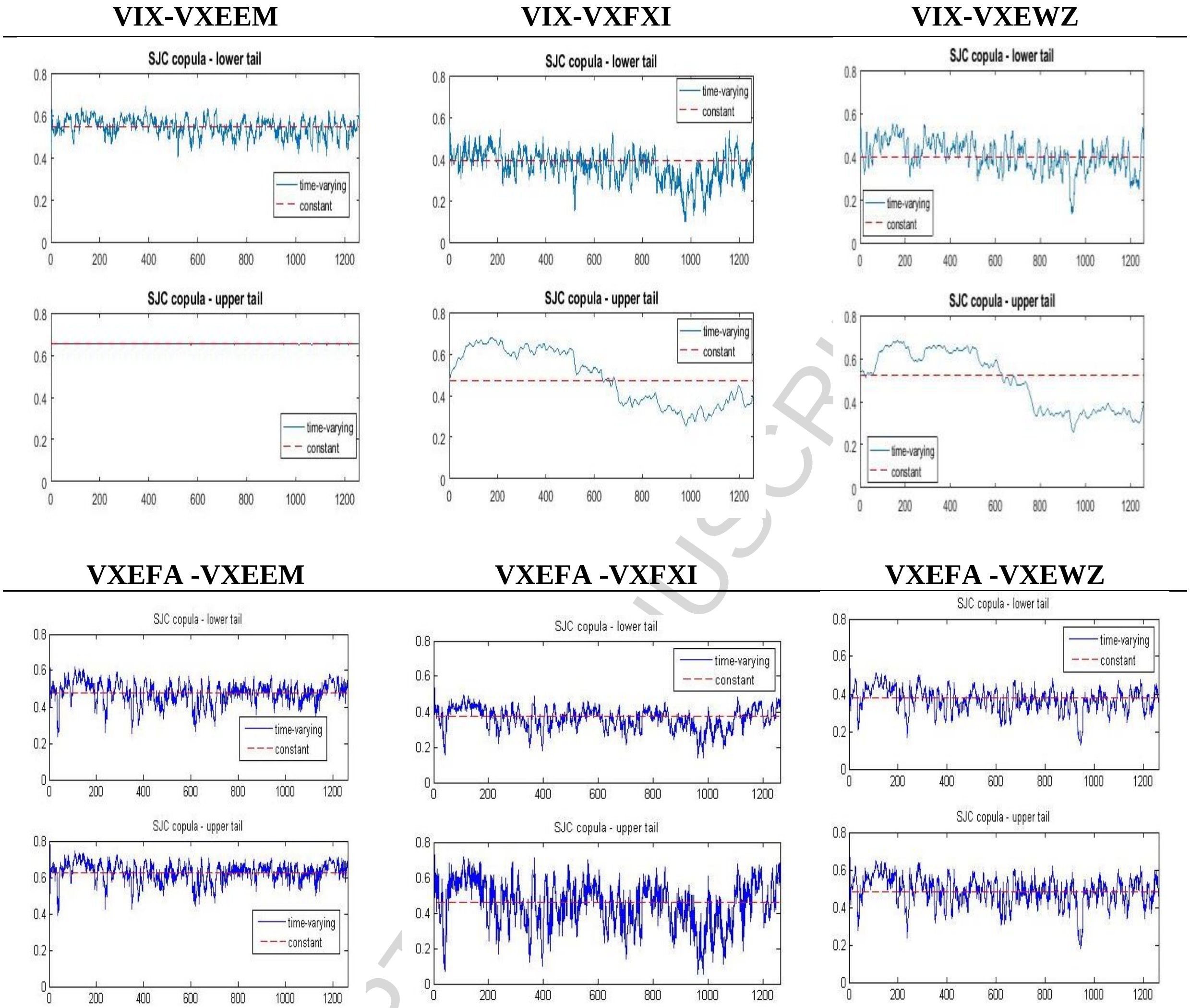






Notes: In the *X*-axis the time period is divided into 200, 400, 600, 800, 1000, 1200 up to 1264 daily obs. corresponding to the following dates: 2011-M_{12}-D_{20}, 2012-M_{09}-D_{25}, 2013-M_{07}-D_{02}, 2014-M_{04}-D_{08}, 2015-M_{01}-D_{13}, 2015-M_{10}-D_{20}- 2016-M_{01}-D_{16} respectively. The sample period spans March 16, 2011 to January 16, 2016.

FIGURE 4: TVP-SJC COPULA DEPENDENCE MEASUREMENT



Notes: In the *X*-axis the time period is divided into 200, 400, 600, 800, 1000, 1200 up to 1264 daily obs. corresponding to the following dates: 2011-M_{12}-D_{20}, 2012-M_{09}-D_{25}, 2013-M_{07}-D_{02}, 2014-M_{04}-D_{08}, 2015-M_{01}-D_{13}, 2015-M_{10}-D_{20}- 2016-M_{01}-D_{16} respectively. The sample period spans March 16, 2011 to January 16, 2016.

Highlights

- We examine the relation between VIX and emerging markets analogs
- This relationship is extremely asymmetric
- This finding is robust to timeperiod, and to estimation methodology