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Full Length Article

Directional predictability in foreign exchange rates of emerging markets: New evidence using a cross-quantilogram approach

Mohd Ziaur Rehman [a,*], Aviral Kumar Tiwari [b,c], Durga Prasad Samontaray [a]

[a] *Department of Finance, College of Business Administration, King Saud University, Riyadh, Saudi Arabia*
[b] *Rajagiri Business School, Rajagiri Valley Campus, India*
[c] *South Ural State University, Lenin Prospect 76, Chelyabinsk 454080, Russian Federation*

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Abstract

This study investigates the directional predictability of exchange rates in emerging markets. Using a cross-quantilogram model, we show that dependencies among emerging markets exchange rates are heterogeneous. Specifically, the Mexican peso, Brazilian real, and Turkish lira are leading emerging market currencies that provide hedging opportunities for currency investors. The structural dependencies across the pairs of exchange rates are evident at lag 1, and the relationships dissipate at longer lags. Secondly, the partial cross-quantilogram results indicate that oil is not a driving force of interrelationship among the exchange rates. Furthermore, the estimations of cross-quantile correlations from recursive subsamples reveal time-variant traits. If policymakers and financial regulators focus on comovements among emerging market currencies and distinguish net recipients from net transmitters in different environments, they can devise a surveillance system to adjust the market interdependence effects across emerging market foreign exchange rates. Therefore, they can promote the stability of emerging market currencies.

JEL classification: C33; F31; O24; E61

Keywords: Emerging markets; Currencies; Exchange rates; Cross-quantilogram; Directional predictability

1. Introduction

Exchange rate dynamics in emerging markets have garnered attention from investors and speculators because emerging market currencies can deliver higher profits than developed economies' currencies due to lower turnover in the former (BIS, 2016). Emerging market currencies represent 25% of overall global turnover across all currencies, helping propel trade in foreign exchange (FX) markets to $6.6 trillion per day in 2019, making FX the largest financial market in terms of size and liquidity. Several studies have confirmed the forte of emerging market currencies relative to developed market currencies (Frankel & Poonawala, 2010; Tajaddini & Crack, 2012).

The percentage of global aggregate foreign exchange turnover involving emerging market currencies rose from less than 2% in 1995 to above 25% by 2019. Consequently, emerging market currencies have been transacted more aggressively, with a larger portion of transactions taking place offshore and in the form of derivatives. Thus, some emerging market currencies have attained a prominent position worldwide. The primary drivers behind emerging market exchange rate changes are spillovers from US shocks, global risk appetite, interest rate effects, and idiosyncratic domestic shocks. Emerging and growth-leading economies (EAGLEs) are a group of eight emerging market countries expected to spearhead global growth and provide significant opportunities for global investors in the coming decade.

* Corresponding author. Department of Finance, College of Business Administration, King Saud University, Riyadh, 71115, Saudi Arabia.
E-mail address: zmuhammad@ksu.edu.sa (M.Z. Rehman).
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Our study covers these eight emerging markets (Brazil, Russia, India, China, Mexico, South Korea, Turkey, and Indonesia). After high inflation and various crises during the 1980s and 1990s, these countries experienced paradigm shifts supported by robust strategies to fortify their economies, mainly focusing on reforms to overcome fiscal deficits, strengthening their banking systems' reliability, and advancing their domestic financial markets.

Our motivation for selecting the eight countries is because these emerging market currencies have the diversification attributes and potential for garnering risk-adjusted returns. Global investors have recognized the forte of emerging market currencies based on their ongoing reforms and integration in the global financial landscape. While these markets' currencies proffer returns, they also expose global investors to the dependence structure dynamics between the purported exchange rates. Thus it is topical to examine and unearth the connectedness among these exchange rates.

A wide range of studies has examined the foreign exchange rate landscape employing various techniques driving to mixed results. The extant literature reveals that the focus has been on the mean and variance of the returns distribution, overlooking the left and right tails. Selected studies indicate nonlinearities and asymmetries in the interdependence of FX markets, including wavelet analysis (Kumar, Pathak, Tiwari, & Yoon, , 2017; Yang, Cai, Zhang, & Hamori, 2016), quantile regression (Kuck & Maderitsch, 2019), copula approach (Albulescu, Aubin, Goyeau, & Tiwari, 2018), cross-quantilogram (Shahzad, Arreola-Hernandez, Bekiros, & Rehman, 2018), and a DCC GARCH (Tamakoshi & Hamori, 2014). These studies suggest FX market returns are tail-driven, mainly in times of extreme volatility.

Considering the non-linear dynamics (Rapach & Wohar, 2006; Christopoulos & León-Ledesma, 2007) and tail dependence (Hartmann et al., 2004) of the financial series, Shahzad, Hernandez, Hanif, & Kayani (2018) and Shahzad, Arreola-Hernandez, Rahman, Uddin, & Yahya. (2020) bring to fore the potent of the cross-quantilogram (CQ) approach and partial CQ (PCQ) in presenting the cross-quantile asymmetries in modeling the exchange rate returns. In this vein, we contribute to the extant literature in the following ways: firstly, the study investigates the dependence structure by modeling the relationships between quantiles of selected emerging-market exchange rates through the CQ by Han, Linton, Oka, & Whang (2016), PCQ, and recursive sampling methods. Secondly, the study investigates under the three market conditions (bearish, normal, and bullish) and different lags structure. This information can help develop investment strategies and portfolio selection based on time horizon (lag structure). Our study further extends previous studies' results revealing the mark of transmission between several emerging markets exchange rates that fluctuate under different market conditions (Le et al., 2018; Shahzad, Arreola-Hernandez, et al., 2018). We focus on the tail distribution of exchange rate returns in emerging markets, which is crucial since investors search for alternative assets capable of offsetting extreme losses in other asset classes.

This study's primary goal is to measure directional predictability during normal and extreme market conditions as determined by three quantiles (the lower, middle, and upper). The magnitude of the coefficient values ranges from highly negative (dark blue) to highly positive (dark red) and are revealed by multicolor bars presented in the lowest part of this study's figures. The quantile cross-correlation heat map is based on calculating the average quantile correlations between countries. The interpretation of quantiles is that lower quantiles (quantile = 0.05) capture adverse market conditions, middle quantiles indicate normal market conditions (quantile = 0.50), and upper quantiles reveal bullish conditions (quantile = 0.95).

Our results reveal four central findings. First, there are various dependency frameworks concerning the directional predictability of exchange rates across emerging markets. Second, the dependency structures between pairs of exchange rates are substantially evident at lag 1, and the relationship dissipates with longer lags. There is no consistent indication of predictability at the medium quantiles. Thirdly, PCQ shows that oil is not a driving force of interrelationship among the exchange rates. Finally, the cross-quantile correlations (CQC) from the recursive subsamples reveal that these correlations are time-variant, mainly in the lower and upper quantiles, revealing an inclination to "dive" and "leap." Thus showing connectedness during periods of strong volatility. The rolling window estimation shows that directional predictability is time-variant. The rest of this paper is organized as follows: Section 2 presents the literature review, Section 3 presents the methodology facets, Section 4 includes empirical results and discussions, and Section 5 suggests policy implications based on our conclusions.

2. Literature review

FX markets are a key axis of the worldwide spread of economic shocks and financial crises; thus, it is relevant to examine FX rates' comovement over various periods. The literature investigating the dependence structure of FX markets is classified into two subareas. One group of studies examined connections among FX rates from the standpoint of volatility and correlation spillovers (Chowdhury & Sarno, 2004; Barunik, Krehlik, & Vacha, 2016; Engle, Ito, & Lin, 1990; Kinkyo, 2020). Inline, a set of studies reveals the varying interdependence of FX markets in the developed economies and the potency of the US dollar with a set of prime currencies (EUR, GBP, CAD, JPY) (Boero, Silvapulle, & Tursunalieva, 2011; Tamakoshi & Hamori, 2014). Of late, similar results were revealed by Albulescu et al. (2018) and Kuck and Maderitsch (2019) too.

Multiple studies investigated FX return comovements and volatility spillovers in European Monetary System currencies before the Euro launched. These studies revealed significant volatility spillovers among European FX rate series during the pre-Euro era (Black & McMillan, 2004). Furthermore, studies show the Euro's role as a leading currency in volatility transmission (Inagaki, 2007; Nikkinen, Sahlström, & Vähämaa, 2006). Inline studies have revealed the dependence structure of European zone currencies with other purported currencies and manifested substantial variation in the range of currency comovements during distressing periods, leading to portfolio gains (Patton, 2006; Kočenda & Moravcová, 2019).

A large part of the literature mainly covers the developed FX markets. Ahmed and Zlate (2014) highlight that less consideration is paid to emerging economies' FX rates. In this vein, studies have covered the Asian region and reveal the presence of exchange rate comovements on account of interdependence (Pandey & Sehgal, 2018; Gomez-Gonzalez & Rojas-Espinosa, 2019).

Another research area on FX market movements pertains to exchange rate returns (Heni & Mohamed, 2011; Jiang et al., 2007; Tai, 2004; Wu, 2007). Our study is related to this strand of literature. Recent studies on exchange rate comovements have revealed that conditional correlations in times of financial distress are considerably greater than during normal times (Loaiza-Maya, Gómez-González, & Melo-Velandia, 2015). Similarly, other studies have revealed substantial variation in correlations over time, with stronger correlation during volatile periods (Dimitriou & Kenourgios, 2013; Dimitriou, & Kenourgios, 2017). Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019), through multivariate copula functions using a regular vine copula approach, showed FX rate contagions for selected economies (UK, Germany, South Korea, Indonesia, Brazil, Chile, and South Africa). Another strand of currency literature through large data coverage (Wang & Xie, 2016; Cao, Zhang & Li, 2017; Wen & Wang, 2020) exhibits volatility and lower and upper tail dependency on the international landscape forex market. A separate group of studies pertains to the topology of correlation networks. Studies employing the purported correlation-based network reveal the US dollar potency in the forex market and territorial clustering on account of global trade and investment (Karmakar, 2017; Kumar et al., 2019; Singh, Nishant, & Kumar, 2018).

In summary, the extant literature reveals the paucity of studies focusing on the whole return distribution covering the tail dependence. Though some studies focus on the copula approach, they fail to cover lags, whereas a CQ approach covers the extreme value dependence with lags. The current paper attempts to lessen this research gap by investigating the directional predictability in the exchange rates of emerging markets through CQ, PCQ, and recursive sampling methods.

3. Methodology

In our study, we define hedge and safe-haven assets as follows. A currency is labeled a hedge if there is no predictability regarding the returns for one exchange rate (the independent rate) to the returns for another exchange rate (the dependent rate) in the tails of their respective distributions when both the exchange rates returns are in a bearish state, defined as the low quantile (threshold = 0.05). In contrast, a currency is marked as a safe-haven if there is evidence of negative return predictability from the independent exchange rate to the dependent exchange rate in both tails (0.05 and 0.95) of the distribution.

By considering different quantile levels, the CQ approach, shown in Han et al. (2016), accounts for non-linear interdependence and predictability between pairs of variables under different market conditions. Quantile-based approaches have three main advantages over linear methods that mainly rely on the average or mean levels of the time series involved. First, the CQ approach is robust to misspecification error as it allows the underlying dependence structure to vary across the distributions of the pair of time series under consideration. Second, the approach is designed to account for the mean level of dependence and measure dependence between the tails of the distributions of the two-time series under consideration. This is an essential aspect, particularly when the distributions of the variables involved are highly non-normal, as in the financial series. Third, these characteristics allow us to capture the dynamics of the dependency between two time series in their entirety, accounting for noise and structural changes in the individual series and the non-linear nature of the relationship between them. (See the Supplementary Material, available online).

4. Empirical results and discussion

4.1. Dataset and preliminary analysis

We use data from Bloomberg for the exchange rates of eight emerging market countries, namely Brazil (BRL), China (CNY), India (INR), Indonesia (IDR), Mexico (MXN), Russia (RUB), South Korea (KRW) and Turkey (TRY) over the period 01/01/2000−09/23/2018, for a total of 4716 observations. The stipulated currency exchange rates are quoted against the US dollar (USD). Studies have revealed that the USD is the utmost adequate currency to which other currencies should be specified (Shahzad et al., 2018, 2020).

Daily returns are defined as the logarithmic differences of the daily exchange rates. Table S1 (see the Supplementary Material, available online) displays the descriptive statistics for the variables selected in this study. The null hypotheses of normality and homoscedasticity are rejected by the Jarque-Bera and ARCH−LM tests, in all variables, at the 1% level of significance. The stationary tests reveal that the variables series are stationary. The presence of high kurtosis exhibits higher chances of extreme returns. It indicates chances of fatter tails than the normal distribution.

4.2. Cross-quantile correlation

This study presents CQC estimates in the form of heat maps for various lag lengths. Heat maps are defined as a graphical representation of the cross-quantile unconditional bivariate correlation between two distributions. The x-axis corresponds to the quantiles of a selected country's exchange rate returns, and the y-axis corresponds to the exchange rate returns of emerging markets. The *x*- and *y*-axes marked by the quantile hits define the quantile distributions [$q = (0.05, 0.1, 0.2, 0.3,$

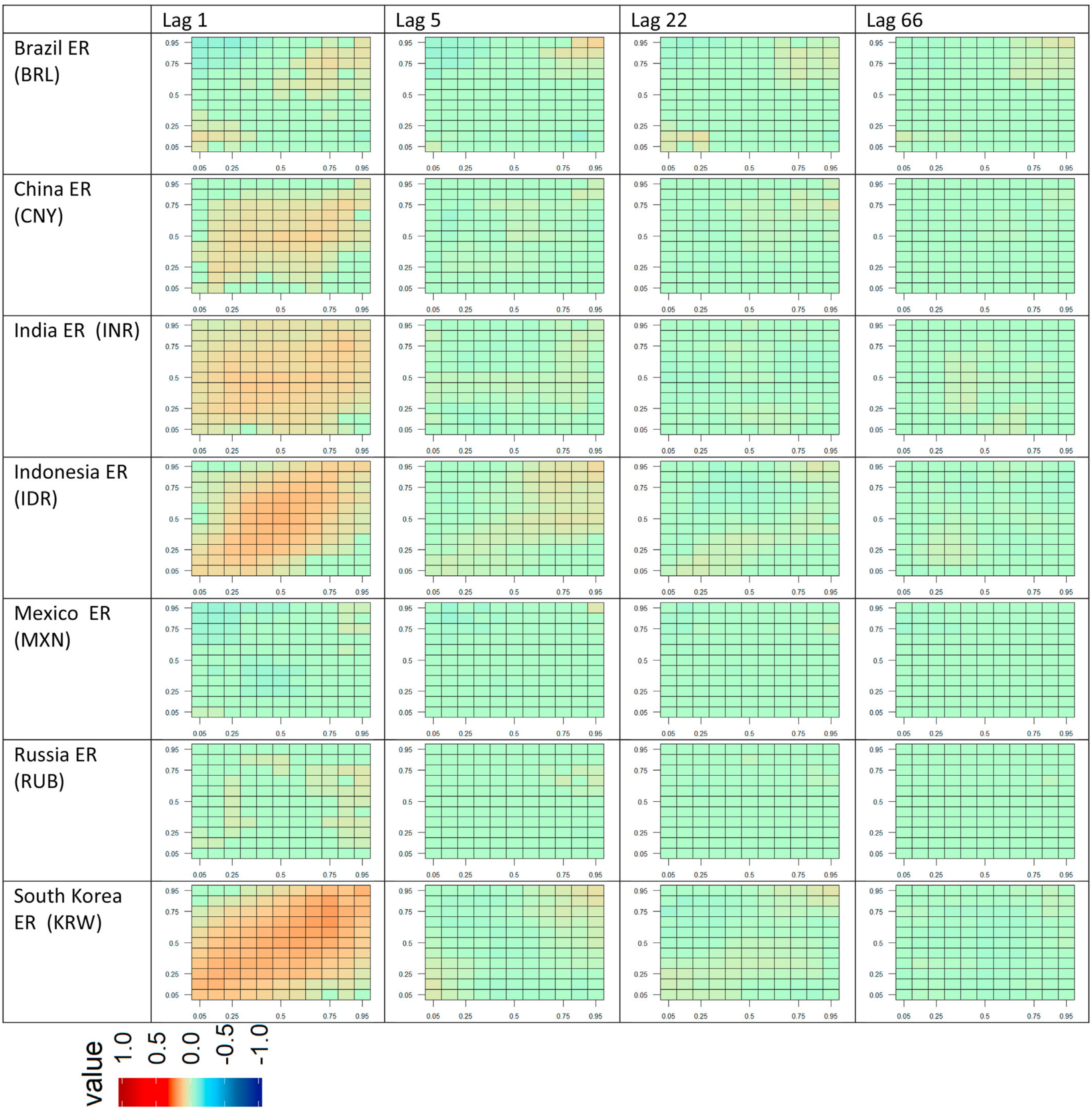
0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95)] of the variables. The quantile combinations of the variables are indicated by 121 (11 × 11) cells in each heat map. A color scale reveals the correlations (ranging from −1.0 to +1.0). A cell where the correlation is zero indicates that the CQC has no predictable directionality. We consider four different lag orders: daily (1 day), weekly (5 days), monthly (22 days), and quarterly (66 days). We use the Box-Ljung test to test for predictability concerning directionality. CQC that are statistically insignificant, indicating a lack of predictable directionality, are set to zero in the heat maps. Overall, this analysis captures quantile dependencies with lags ranging from daily to quarterly. This information can help develop investment strategies and portfolio selection based on time horizon (lag structure). Eight figures cover the cross-quantile dependence between the emerging market exchange rates. Several broad observations are noticed from the results. First, there are almost no predictable correlations within the middle quantiles of the distributions. This may indicate that: (i) "normal" exchange rate returns in one emerging market barely impact the exchange rate return distribution of another emerging market, and (ii) other factors could drive exchange rate returns in emerging markets. Second, the dependence of emerging markets exchange rate returns in terms of quantile-based responses fluctuates for each currency, indicating links between specific pairs of emerging markets currencies are key to shaping the various market reactions. Third, the heat maps reveal a steady quantile dependence at lag 1 that wanes as the lags increase.

Fig. 1 presents the directional predictabilities in quantiles from Turkish exchange rate returns to the selected emerging markets' exchange rate returns. The CQC reveals that red dominates the heat map for the TRY versus KRW at lag 1. This indicates a positive relationship between their FX returns across low, medium, and high quantiles of the distribution, although, with longer lags, the relationship weakens. There is evidence of positive predictability between the TRY and RUB, with similar TRY and CNY, INR, and IND results. This indicates that none of these four emerging market currencies are a good source of diversification for TRY investors. The heat maps for the TRY and BRL, and the TRY and MXN show a mix of red and blue, indicating a negative relationship in the upper right corner. Thus, the correlation between the currency returns for these pairs oscillates between positive and negative. In the upper quantile of TRY returns, there is positive predictability for Brazil and Mexico. With lag 1, Turkey's FX returns' lower quantiles negatively correlate with Brazil and Mexico's FX returns at the upper quantiles for those countries. Thus, over a short time horizon, Brazil and Mexico's FX returns offer good diversification for TRY investors. Overall, the results show that FX returns for six out of the seven emerging markets analyzed are tail-driven concerning correlations with Turkey's FX returns. This indicates a tendency for these currencies to experience dramatic increases and declines over the short-term. That is, there is short-lived directional positive predictability in these cases. Extreme negative returns for the TRY are associated with extreme negative FX returns for Mexico and Brazil. In contrast, extreme negative (lower quantile) TRY returns predict extremely positive (upper quantile) returns for Brazil and Mexico. These results appear contradictory, but they show the quantile causality in these currency pairs varies over time.

Figure S1 (see, available online) shows directional predictabilities in quantiles from Brazil's exchange rate returns. The CQC heat maps for five pairs of exchange rate returns involving the BRL and the other emerging market currencies are dominated by red. The positive relationship is highly significant for Brazil FX-India FX, Brazil FX-Indonesia FX, and Brazil FX-South Korea FX. The positive sign in the upper right corner of these heat maps reveals that a decrease (increase) in Brazil FX returns is likely to be followed by a decline (increase) in FX returns with India, Indonesia, and South Korea. These FX markets are likely to decline sharply and surge together, indicating that these three currencies would not be a good hedge for the BRL. Similar positive relationships for the BRL with the CNY and RUB are revealed at lag 1, indicating that Russia and China are also not good sources of diversification. However, at subsequent lags, the blue color in some quantiles indicates a negative relationship, indicating the potential for those currencies to serve as hedges over longer periods. For Turkey and Mexico, the heat maps show a combination of red and blue. The blue in the extreme upper left quantile associates extremely negative FX returns in the BRL with future positive FX returns against the MXN and TRY. These currency pairs are likely to move in opposite directions under those extreme conditions, suggesting the MXN and TRY could be safe-haven currencies for BRL investors. In the subsequent lags, the pattern is maintained, although the strength of the relationship is weaker.

Figure S2 (see, available online) shows directional predictability in quantiles from China's exchange rate returns. In the first row under lag 1, the lower, medium, and upper quantiles for the CNY positively correlate with the lower, medium, and upper quantiles for the BRL, indicating Brazil's positive dependence on China during bearish, normal, and bullish conditions. There is scattered evidence of positive predictability with subsequent lags (5 and 22), although the latter directional impact almost disappears. The second row shows that the upper (lower) quantile for the CNY negatively correlates with the INR's lower (upper) quantile. In contrast, the lower (upper) quantile for the CNY positively correlates with the INR's lower (upper) quantile. Longer lags reveal homogeneous dependence. The same pattern is evident for the CNY and RUB, while positive and scattered patterns are seen for the CNY relative to the INR and MXN, respectively. Though the upper quantile for China positively correlates with the KRW with lag 1, the relationship becomes weak with subsequent lags. There is a modest negative correlation between the lower quantiles for the CNY and various quantiles for the TRY, though at longer lags, there is no dependency.

Figure S3 (see, available online) displays India's exchange rate returns. The CQC heat maps show a positive relationship between the INR-KRW and between the INR-IDR at various quantiles, although the relationship is weaker with higher lags. Thus, the correlation structure is unappealing for hedging purposes. In the case of the INR-CNY, MXN-RUB, both blue and red appear in the tail regions; the lower left and upper right corners reveal positive relationships, indicating that India FX returns relative to the CNY, MXN and RUB are likely to experience extreme movements together. Relative to these three currencies, the FX rate moves in the upper left quantiles for the INR are blue. In contrast, those in the lower-left quantiles are red, showing that the INR's extreme negative moves are associated with extremely negative and positive FX returns versus the CNY, MXN, and RUB. The coexistence of these contradictory results reveals the changing nature of these three currencies. The blue areas in the extreme upper left quantile for China, Mexico, and Russia means these currencies can be a safe-haven when the INR declines. This trend continues with



Notes: this figure displays the cross-quantile correlations in heat maps form. The horizontal axis refers to the quantile of Turkey exchange rates returns and the vertical axis corresponds to the exchange rate returns of the selected emerging markets. The color bar reported at the end of the figure indicates the strength of the magnitude of the cross-quantile correlation coefficients. (For the interpretation of the references to color in this figure legend, we refer the reader to the web version of this article).

Fig. 1. Directional predictabilities in quantiles from **Turkey** and FX returns for the other emerging markets.

subsequent lags for both China and Russia. In Brazil and Turkey, limited scattered red areas are revealing weak positive relationships; thus, there is no particular pattern in the case of BRL returns and TRY returns relative to INR returns.

In Figure S4 (see, available online), the CQC analysis for Indonesia shows green dominating, indicating a low dependency between Indonesia FX returns and other emerging market FX returns. The IDR to CNY returns reveals negative (positive) predictability for the lower/lower (upper/upper) quantiles. In contrast, there is a positive correlation between the lower (upper) quantiles for the IDR and the upper (lower) quantiles for the CNY at lag 1 and all subsequent lags. There is also evidence of positive predictability for Indonesia and the KRW for lag 1. Indonesia FX returns reveal a lack of influence on returns for the INR and MXN across all quantiles and lags. TRY returns in the uppermost quantiles respond negatively to the lower IDR quantile returns for lags 1 and 5. In subsequent lags, the heat map is green, indicating there is no dependence between the two. Like the TRY, the IDR returns show a negative relationship with the BRL at lag 1, but there is no dependence in subsequent lags. For the RUB, there are scattered patches of red revealing a weak positive relationship. As there is no predictability in the extreme lower left and upper right, the RUB could be an effective hedge for the IDR.

In Figure S5 (see, available online), the CQC analysis for Mexico manifests that the selected emerging markets' FX returns tend to be positive. However, there are substantial differences among the currency pairs regarding the correlations' strength and structure. Through the heat maps, tail event dependencies between Mexico and five of the emerging markets exist. Red dominates across most of the quantiles, revealing strong positive dependencies with South Korea, Indonesia, India, China, and Russia. These findings indicate that those countries' currencies would not be effective hedges against a downturn in the MXN at lag 1. For Mexico and Indonesia, most of the high correlation values are concentrated in the medium quantiles. For MXN and TRY returns, there is a lack of dependency across all quantiles and lags. For Mexico and Brazil, the green extending over the entire range of quantiles shows the lack of dependence between their FX returns, indicating a hedging opportunity.

In Figure S6 (see, available online), provides Russia's exchange rate returns. The CQC heat maps for the RUB versus South Korea, India, Indonesia, and Brazil are dominated by red. The CNY and MXN have a blend of blue and red in the heat maps; the blue areas might be effective hedges in the case of a decline in the RUB. These apparently contradictory results reveal FX returns' changing nature for the MXN and CNY relative to the RUB. The same pattern appears at all subsequent lags, indicating the existence of long-lived predictability. In the RUB and BRL currency pair, the red areas in the upper right quantile indicate positive dependence between the two. The pattern is maintained at subsequent lags, indicating long-lived predictability, although the BRL may not be a good hedge. Regarding the TRY, there is no overall dependence with the RUB, indicating a good source of diversification at all the lags for investors.

In Figure S7 (see, available online), shows South Korea's exchange rate returns. Through the CQC, six emerging markets' FX returns have blue and red areas in their heat maps. There is a strong quantile dependence in only a few quantiles at lag 1. The CQC's shift from positive to negative for all except Indonesia, revealing asymmetric dependencies as the South Korean currency experiences a decline (lower quantile) compared to when it is stable (middle quantile) and strengthens (upper quantile). The dependence exists primarily in the extreme lower and upper quantiles of the dependent and independent FX rates. The lowest quantile of South Korean FX returns positively (negatively) predicts the FX returns for six emerging markets currencies in the lower (upper) quantiles. These relationships in the tail quantiles but not around the mean supports using the CQ method. The heat maps for all seven emerging markets FX returns have red areas in the lower-left corner, revealing extreme negative FX returns for South Korea, typically induce negative future returns in all other emerging markets currencies included in the study. This finding indicates that FX returns for these currencies cannot be a hedge against a downturn in the KRW. The blue areas in the extreme upper left and lower right corners for five currencies indicate a negative relationship. Thus, extreme negative returns for the KRW should also predict extreme positive FX returns for five of these emerging market currencies. These findings appear contradictory, but this demonstrates that the emerging markets' FX returns can change and their ability to serve as hedges or safe-havens depends on the distribution of returns. Regarding the KRW, the MXN, RUB, and TRY exhibit the same trends across all the lags, revealing long-lived directional predictability. For the CNY and BRL, the pattern is consistent up to lag 22 (one month), while the INR and IDR have extremely limited amounts of either blue or red in the heat maps at longer lags.

In conclusion, we find that the cross-quantile dependence between emerging markets currencies is fundamentally short-term. The dependence wanes as the lags time increases. Thus, these results are most relevant for near-term capital providers. Selected studies have revealed that short-term linkage across emerging markets (Ahmad, Sehgal, & Bhanumurthy, 2013; Aroul & Swanson, 2018). Concerning hedging opportunities, in order of significance, we find that the MXN is the most desirable currencies for diversification for downturns in the BRL, followed by the INR, RUB, KWR, and TRY. Secondly, the BRL could be used to hedge downside risk for the IDR, MXN, KWR, and TRY. Thirdly, the TRY may be useful for hedging declines in the BRL, CNY, IDR, and KRW. The INR and RUB can act as diversifiers for declines in the CNY and KWR.

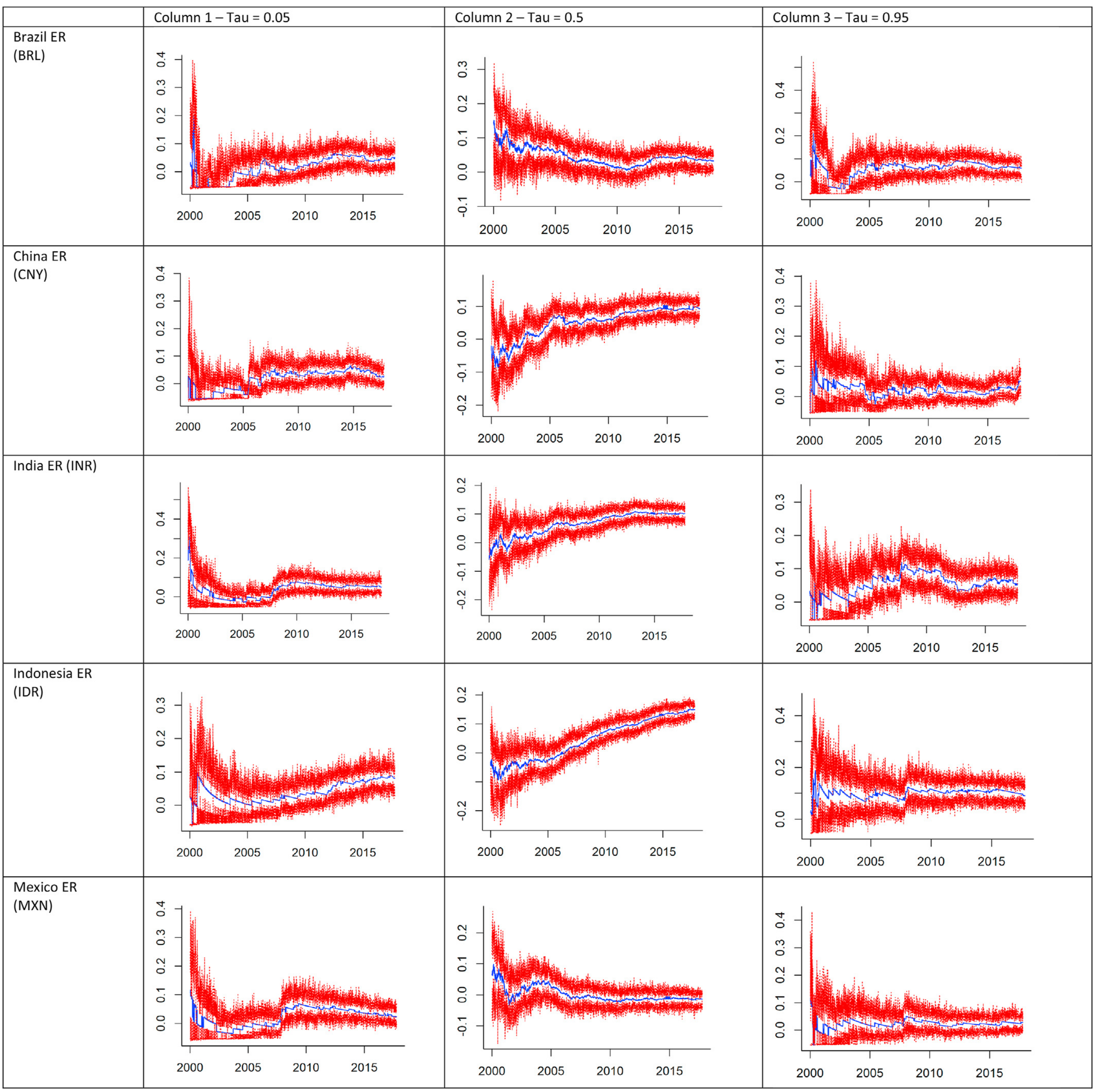
4.3. Cross-quantile correlations after incorporating controlling variable (oil)

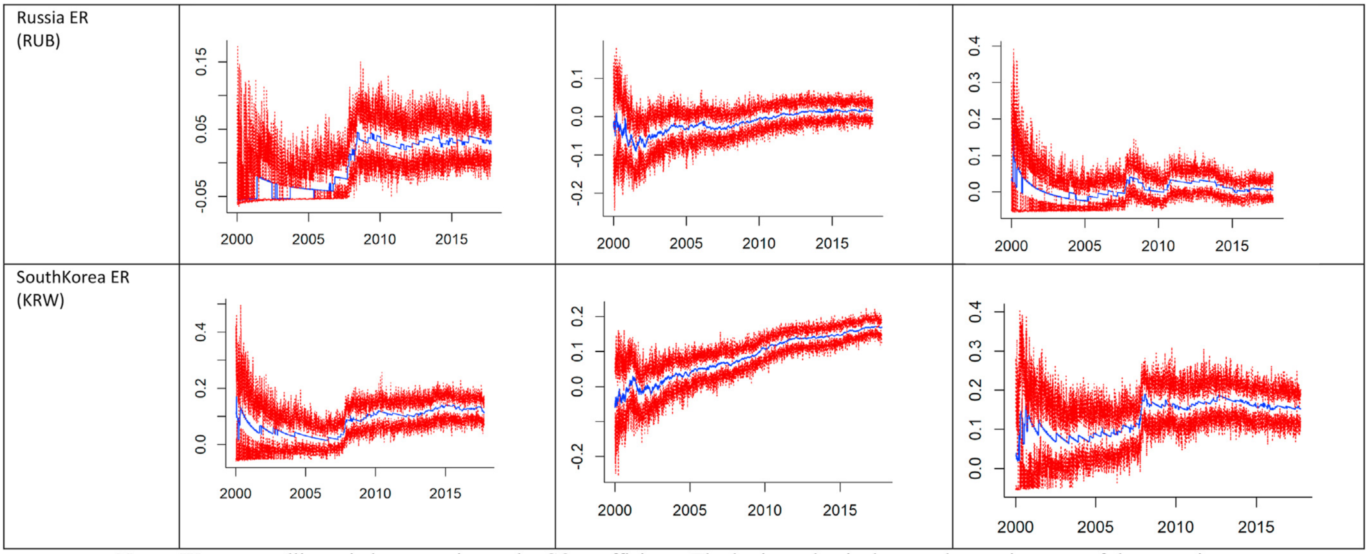
Studies have underlined the implication of transmission of oil shocks towards the exchange rates. Živkov, Njegić, & Balaban, (2019) and Nusair and Olson (2019) reveal that oil price shocks deliver an asymmetrical impact on exchange rate returns. The studies highlight substantial coherence between oil prices and exchange rates through the severe market turmoil. Thus international investors need to consider the oil factor while configuring the portfolio. Inline, PCQ model estimation is done, Brent oil is considered as an interconnection between the purported variables on account of underlying variations in the oil price. Figures S8 and S9 (see, available online), present the PCQ estimations between the emerging markets exchange rates controlling for Brent oil.

Overall, Figures S8 and S9 show that Brent oil has a low or insignificant impact on the CQC between the purported emerging market exchange rates. Thus, oil is not a driving force of interrelationship among the exchange rates. Additionally, it is reinforced that the endogenous interlinkage is the prime driver for the intrinsic CQC effects. To conserve space, we limit our analysis on PCQ to two figures.

4.4. Cross-quantile correlations from a recursive subsample

Next, to analyze whether there is time-dependency in our FX returns correlations, we break our entire dataset into subsamples using a rolling window. We create the first subsample period with the first 250 days of observations, spanning 01/02/2000−12/18/2000, then move one day forward so that the





Notes: We use a rolling window to estimate the CQ coefficients. The horizontal axis denotes the starting year of the recursive subsampling. The second, third, and fourth columns refer to quantiles 5% (lower), 50% (median), and 95% (upper), respectively. The blue lines show the time-varying CQ coefficients over the recursive subsampling procedure. The red lines show a 95% bootstrapped confidence interval for the absence of predictability based on 1,000 bootstrapped replications

Fig. 2. Rolling window quantile dependence between **Turkey** and other emerging markets FX returns.

second subsample spans 01/03/2000−12/19/2000. This process continues until the end of the sample period, October 12, 2018. A total of 4649 rolling window subsamples for estimating CQC is formed. We provide detailed results of the CQC obtained using these subsamples for the eight emerging markets. These figures show the time-varying dependence for each country relative to the other countries. The horizontal axis denotes the starting year of the recursive subsampling. The second, third, and fourth columns refer to the quantiles, 5% (low), 50% (median), and 95% (high), respectively. The red lines show a 95% confidence interval using the bootstrap procedure for the absence of predictability based on 1000 bootstrapped replications. The blue lines show the time-varying CQ coefficients over the recursive subsampling periods. The following is an analysis of the quantilogram correlations before, during, and after the 2008 global financial crisis for the low, medium, and high quantiles.

Fig. 2 shows the rolling window subsample quantile dependence between the TRY and other emerging markets exchange rate returns. The CQC between TRY-BRL and TRY-CNY depicts a positive correlation throughout the sample period, with a slight dip and volatility in the early 2000s. The TRY-INR and TRY-IDR depict positive correlations in the early 2000s and after 2008. During 2003−2008, there was only a weak (roughly zero) correlation in the lower quantile and positive correlations throughout the upper quantiles periods. The TRY-KRW reveals a volatile and positive relationship in all quantiles. The TRY-MXN show a negative CQC until 2005 in the lower quantile and a weak but volatile relationship in the upper quantile. The correlation between the TRY-RUB is negative until 2008 and reverses thereafter in the lower quantile. It is erratic but positive in the upper quantile except for 2003−2005.

In Figure S10 (see, available online) shows the rolling window subsample quantile dependence for the BRL. The quantilogram correlations (in blue) for the lower quantiles, i.e., plotting both variables at their 5% quantiles, are shown in the first column. We have a significant relationship only when the blue line exceeds the band between red lines. There we found negative CQCs between the BRL-CNY, BRL-INR, and BRL-RUB in the lower quantile, occurring in 2000−2006. We find many fluctuations in correlations between the BRL-KRW during 2000−2009, with a positive CQC thereafter. There was a positive correlation between the BRL-IDR and BRL-TRY during the early 2000s, but it was not sustained. A positive correlation is also seen for the BRL-MXN during 2007−2018. Studying the median quantilogram correlations in the median quantiles in Column 2 of Figure S10 (plotting the median quantiles for both variables), we find the CQC between the BRL-IDR is positive, whereas BRL-MXN is negative throughout the sample period. The CQC is positive for the BRL- KRW, and BRL-TRY after the year 2002 and continued till the end of the sample period. The correlation between the BRL-CNY is negative for 2000−2007 and positive thereafter. The correlation between the BRL-INR is unstable until 2007 with a positive trend thereafter. Similarly, we studied the upper quantile correlations in the last column of Figure S10 and observed negative correlations for the BRL versus the INR from 2000 to 2007 and versus the RUB and IDR from 2000 to 2006.

Figure S11 (see, available online) depicts rolling window subsample quantile dependence for the CNY. China's FX returns versus the BRL show a negative CQC spanning 2004−2008 in the lower quantile (5%), during 2001−2003 in the middle quantile (50%), and from the year 2006 in the upper quantile. China's FX returns versus the INR are negatively correlated up to 2006 in both the lower and upper quantiles. Similarly, we see a negative correlation between China's FX returns and the IDR from 2007 through the end of the sample period in the lower quantile. Relative to the MXN, the correlation is negative over 2005–2011 in the lower quantile and early 2000s in the medium and upper quantiles. Simultaneously the correlation between China's FX returns and the RUB, KRW, and TRY were either unstable or close to zero, depending on the quantile.

Figure S12 (see, available online) depicts the rolling window subsample quantile dependence for the INR. The INR correlation with the BRL in the lower quantile is positive except for a negative correlation over 2004–2008. In the higher quantile, the correlation moved from negative to slightly positive after 2007. Comparing the INR returns to the CNY, we see volatility in the CQC up to 2010 in the lower and upper quantiles. The correlation between the INR and TRY is close to zero in the lower medium and upper quantiles. The INR shows a positive correlation with the IDR in the middle quantile, whereas we see volatility in the lower quantiles and positive volatile CQC in the upper quantiles. For the INR-MXN, we find volatility CQC in the lower and upper quantiles and positive volatile CQC for the entire sample period in the case for the INR versus the RUB and KRW in the lower and uppers quantiles.

Figure S13 (see, available online) depicts the rolling window subsample quantile dependence for the IDR. The correlation with the BRL is slightly negative and volatile in the lower, median, and higher quantiles in the earlier years of the sample period. The IDR CQC with the CNY is volatile and positive up to 2005; afterward, it is negative in both the lower and upper quantiles. The IDR-INR and IDR-RUB exhibit a volatile positive relationship up to 2006. After that, there is no significant correlation in any quantile. The IDR is uncorrelated with the MXN and TRY in all the quantiles. For the KRW, we found no correlation up to 2007 followed by a positive correlation afterward in the lower quantile, while the relationship is reversed in the median and upper quantiles.

Figure S14 (see, available online) depicts the MXN. Analyzing the CQC pattern versus the BRL, we see the correlations in all the quantiles are volatile up to 2007 and positive after that. The CQC for the MXN-CNY shows an erratic and negative relationship up to 2006 in the lower quantile and unstable but positive correlations in the upper quantile. The MXN-INR correlation is positive and volatile in the lower and upper quantiles up to 2010 and stable after. The MXN-IDR rolling correlations are negative up to 2007 in the lower quantile but volatile and positive in the upper quantile, stabilizing after 2007. The correlation between the MXN-RUB is mostly positive but erratic in both the lower and upper quantiles. The MXN-KWR relationship is volatile, jumping from close to zero to a positive relationship in 2007 and afterward in the lower quantile. Increasingly positive over the sample period for the median and upper quantiles. A positive but volatile relationship is seen before 2007 for the MXN-TRY in the lower quantile but negative in the higher quantile for the same period.

Figure S15(see, available online) depicts the RUB. Examining the CQC for the RUB-BRL, the correlation is highly volatile and mostly negative up to 2007, turning positive in both the lower and upper quantiles. For the RUB-CNY, we see a volatile positive relationship with large moves during 2006–2008 in the lower and upper quantiles. Studying the CQC between the RUB-INR, RUB-IDR, RUB-KWR, and RUB-MXN shows weak but volatile correlations until 2008, then turning positive in the lower and upper quantiles. Usually, we see insignificant CQC between the RUB-TRY.

Figure S16 (see, available online) depicts the KRW. The CQC between the KRW-BRL is positive across almost the entire period in the lower quantile, positive in the median quantile, and slightly positive in the upper quantile. The IDR-MXN has similar relationships with the KRW in the lower and upper quantiles, negative until 2008 and positive. The KRW has a negative and erratic relationship with the CNY, INR, and RUB until 2008 in the lower and upper quantiles, followed by roughly zero correlation afterward. There are no notable trends between the KRW-TRY.

After a thorough investigation and analysis of the CQCs using recursive sampling, we offer the following observations: The CNY is the most desirable currency for achieving diversification with the INR, IDR, MXN, KRW, and TRY. The BRL offers diversification benefits for the INR, MXN, RUB, and KRW. Similarly, the INR offers diversification versus the CNY, BRL, MXN, and KRW. The MXN could be hedged using the CNY, BRL, INR, and IDR. The KRW and TRY show similar diversification patterns with the BRL, CNY, INR, and RUB. Hedging strategies for the IDR could be effective using the CNY, MXN, and KRW. We found the lowest diversification benefits between the RUB, TRY, and KRW.

5. Conclusion and policy implications

The comovement in FX rates received a great deal of attention due to the practical importance of the currency comovements concerning economic policies (Nikkinen et al., 2011; Yang et al., 2016). Studies have revealed that emerging markets' currencies have attained global significance based on a central role in global reserves, active FX trading, and involvement in global trade and financial transactions (Ahmed, Wang, Mateos y Lago, Maziad, Segal, Farahmand, & Das, 2011). This study examines the directional predictability in exchange rates for emerging market currencies to add to the literature. This paper's central contribution is the employment of the CQ model proposed by Han et al. (2016) to analyze quantile-based dependence between two stationary variables. Secondly, we cover the PCQ model by incorporating Brent oil to investigate the impact on the exchange rates' dependence structure. Furthermore, the study estimates the CQC for recursive samples to know the time-variant traits in the linkage exchange rates.

Several findings stem from our analysis. Firstly, the dependencies between emerging market FX returns are largely heterogeneous. Among this study's eight currencies, the MXN, BRL, and TRY are the leading currencies to provide hedging opportunities for emerging market currencies investors. Secondly, the dependency structures between currency pairs are substantially evident at lag 1, but the relationships dissipate with longer lags, and there is little evidence of predictability in the median quantiles. Thirdly, through PCQ, oil is not a driving force of inter-relationship among the exchange rates. Lastly, CQCs computed from recursive subsamples reveal that CQCs are time-variant, mainly in the lower and upper quantiles, showing an inclination for pairs of currencies to exhibit strong moves in the tails distribution at different periods, indicating connectedness during periods of turmoil and showing directional predictability is time-variant.

The dependencies between emerging markets FX returns are an important issue for portfolio diversification across currencies. Investing in different currencies provides diversification benefits when the currencies display negative or low correlations. The CQC helps to understand the comovements of assets, thus informing portfolio diversification and investment decisions. From an asset allocation viewpoint, investors should consider modifying their portfolios in the presence of strong, positive dependencies during periods of market turmoil. FX market linkages are enhanced by liberalizing trade and investment policies, and market flows into emerging markets have increased considerably over time. Thus, emerging market currency investors may search for safe-haven currencies. Understanding the dependency structures of emerging market FX movements offers an opportunity to improve asset allocation and create better risk-adjusted portfolios. In terms of emerging markets currency stability, policymakers and financial regulators can benefit from a better understanding of net recipients and net transmitters of currency movements by understanding the comovements of their home currencies and other emerging markets currencies. The ability to distinguish net recipients from net transmitters of FX movements in emerging markets under different phases can allow policymakers and regulators to devise a surveillance system for adjusting market interdependence effects concerning the impact of FX moves in emerging markets.

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Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2021.03.003.

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