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Analyzing Exchange Rate Dynamics within the Global Financial Cycle: A DCC-Copula approach*

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Abstract

The Global Financial Cycle (GFC), defined as the fluctuations in international capital flows, asset prices, and risk appetite, has garnered significant attention from the recent international finance literature, market practitioners, and policymakers. This study employs a Dynamic Conditional Correlation (DCC) Copula model to examine the interaction between exchange rates for a group of seven developed economies and seventeen emerging market economies. Using these results and employing quantile panel data methods, we assess how the time-varying correlations of exchange rates behave in relation to variables associated with the GFC, specifically the VIX. The findings contribute to understanding the interconnectedness between time-varying international financial conditions and currency markets over time and during stress episodes, offering relevant implications for policymakers and market participants.

Keywords: Dynamic conditional correlations, Elliptical copulas, Exchange rates, Global Financial Cycle.

JEL Codes: C22, C46, F31, G15.

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Análisis de la Dinámica de las Tasas de Cambio en el Contexto del Ciclo Financiero Global: Un Enfoque con Modelos DCC-Cópula

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Resumen

El Ciclo Financiero Global (GFC), definido como las fluctuaciones en los flujos internacionales de capital, los precios de los activos y el apetito por el riesgo, ha captado una atención significativa por parte de la literatura reciente en finanzas internacionales, los analistas de mercado y los responsables de política económica. En este estudio emplean modelos de Cópulas con Correlaciones Condicionales Dinámicas (DCC, por sus siglas en inglés) para examinar las correlaciones entre las tasas de cambio de un grupo de siete economías desarrolladas y diecisiete economías emergentes. A partir de estos resultados y utilizando métodos de datos de panel cuantílicos, se evalúa cómo se comportan las correlaciones dinámicas de las tasas de cambio frente a variables asociadas al GFC, en particular el índice VIX. Los hallazgos contribuyen a una mejor comprensión de la interconexión entre las condiciones financieras internacionales y los mercados cambiarios, tanto a lo largo del tiempo como durante episodios de estrés, ofreciendo implicaciones relevantes tanto para los responsables de política como para los participantes del mercado cambiario.

Palabras clave: Correlaciones condicionales dinámicas, Cópulas elípticas, Tasas de cambio, Ciclo Financiero Global.

Códigos JEL: C22, C46, F31, G15.

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1 Introduction

Global financial conditions exhibit a cyclical pattern in which international asset prices, credit, and capital flows fluctuate in response to global factors and investor appetite for market risk (Obstfeld and Zhou, 2023; Habib and Venditti, 2018). This phenomenon, known as the Global Financial Cycle (GFC) (Miranda-Agrippino and Rey, 2022), drives common movements in risky asset prices, with significant implications for exchange rates.

Given the nature of the definition of this concept, Rey (2016) and Miranda-Agrippino and Rey (2022) estimated the GFC using a common factor approach. They also highlighted the correlation between this common factor and the VIX index, a widely used measure of risk and risk aversion. Figure 1 shows this relationship between the common factor of asset price movements and the VIX index.

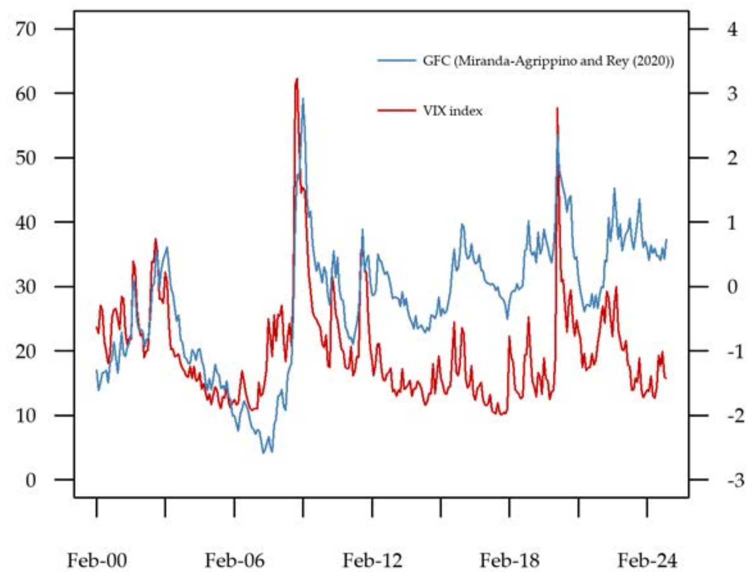


Figure 1: VIX index vs. Common factor across world risky asset prices.

Source: Bloomberg and Miranda-Agrippino and Rey (2020). The GFC common factor is scaled such that increases in the index indicate a deterioration in global financial conditions. The scale of the VIX index is shown on the left Y-axis, while the scale of the GFC is indicated on the right Y-axis.

Understanding the transmission of the GFC to the exchange rate markets is crucial. Furthermore, understanding how exchange rate correlations evolve is central to portfolio diversification. Previous research (Miranda-Agrippino and Rey, 2022; Obstfeld and Zhou, 2023) have shown that fluctuations in global risk appetite, using VIX as a proxy variable, are associated with movements in exchange rates, particularly during periods of financial stress. Furthermore, the dominant role of the US dollar in global finance suggests that dollar appreciation during global downturns tightens financial conditions globally, amplifying the effects of the GFC.

Most of the GFC literature has focused on the first moments, particularly levels or changes in asset prices, capital flows, and credit growth. In contrast, this study examines how the GFC influences the comovement of asset prices, with a particular focus on exchange rates. In this context, our contribution to the literature is threefold. First, we document the evolution of exchange rate correlations using DCC-Copula models for an ample set of currencies. Second, we show that these correlations are significantly influenced by variables related to the GFC, namely, the VIX index. Third, we find that highly correlated currencies are more prone to be affected by the GFC.

Our findings contribute to the literature on international macroeconomics by providing empirical evidence on how global financial conditions influence exchange rate returns and pairwise exchange rate correlations, particularly in periods of financial turbulence. These results have important implications for market participants and policymakers, as they provide an additional approach to FX diversification. Methodologically, our study uses a Dynamic Conditional Correlation Copula (DCC-Copula) model to analyze the interaction between the exchange rates of seven developed economies and seventeen emerging market economies. Based on these results, we employ quantile panel data methods to assess how the time-varying correlations of exchange rates are affected by variables associated with the Global Financial Cycle, specifically the VIX.

The remainder of this paper is organized as follows. Section 2 discusses the relevance of the GFC on exchange rate dynamics. Section 3 outlines the data and econometric methodologies used in our study. Section 4 presents a discussion of the empirical findings, while Section 5 concludes with implications for policy and suggestions for future research.

2 The Importance of the GFC in Exchange Rate Analysis

The skepticism regarding the predictability of exchange rates, as highlighted in the Meese and Rogoff puzzle (Meese and Rogoff, 1983a,b), remains a central issue in empirical research. Rossi (2013) reviews the literature on exchange rate forecastability and highlights that, while traditional models often underperform relative to simple random walk benchmarks, forecast accuracy improves under certain conditions, particularly when models incorporate Taylor rule fundamentals or net foreign assets and adopt parsimonious specifications. However, predictability remains conditional on factors such as sample period, forecast horizon, and choice of predictors, underscoring the inherent complexity of exchange rate determination.

Against this backdrop, the concept of the GFC, introduced by Rossi (2013) and further developed by Miranda-Agrippino and Rey (2022), added a compelling macro-financial layer to exchange rate analysis. The GFC captures the synchronized movement of asset prices, capital flows, and leverage across countries, primarily driven by global risk appetite and U.S. monetary policy. Dynamic factor models estimate that a single global factor—closely aligned with volatility indices and international investors' risk appetite, such as the VIX — explains a significant share of global asset price variation. In addition, Miranda-Agrippino and Rey (2022, 2020) demonstrated that a tightening in U.S. monetary policy triggers deleveraging by global financial intermediaries, which reduces international credit provision and tightens financial conditions globally, even in economies with floating exchange rate regimes, thereby contributing to the GFC.

The implications for exchange rates are twofold. First, the GFC imposes a common global financial constraint, reducing the autonomy of domestic monetary policy and limiting the insulation typically afforded by exchange rate flexibility. Miranda-Agrippino and Rey (2020) show that financial spillovers from U.S. monetary shocks affect global financial conditions through synchronized risk premia, capital flows, and credit movements. Second, the comovement patterns captured by the GFC imply that exchange rate behavior may reflect changes in global risk-taking and liquidity conditions beyond local macroeconomic fundamentals, particularly during risk-on/risk-off episodes.

Furthermore, Obstfeld and Zhou (2023) state that:

> *The U.S. dollar's nominal effective exchange rate closely tracks global financial conditions, which themselves show a cyclical pattern. Over that cycle, world asset prices, leverage, and capital flows move in concert with global growth, especially influencing the fortunes of emerging and developing economies.* (Abstract, parag. 1)

These insights suggest that global financial variables, particularly measures of global risk aversion and the stance of U.S. monetary policy, are important elements for understanding and forecasting exchange rate dynamics. However, Habib and Venditti (2018) note that despite a global factor that closely tracks changes in global financial conditions that may affect international financial markets and capital flows, there is a large degree of heterogeneity in the sensitivity of each country to this same global factor.

In this context, this paper is related to the recent literature on the effects of the GFC on exchange rate dynamics. This area of research has explored the significant role that the USD currency plays in the propagation of U.S. macroeconomic news and risk aversion(Rey et al., 2024), the role of the U.S. dollar in monitoring global financial conditions, and how dollar appreciation shocks predict declines in output, consumption, investment, and government spending in emerging market economies (Obstfeld and Zhou, 2023), the role of demand for the U.S. dollar as a safe asset and the close relationship between the dollar cycle and the GFC (Jiang et al., 2024), and the role of the dollar for the transmission of global risk to the world economy (Georgiadis et al., 2024). However, our approach contributes to the literature by providing evidence of how the GFC affects pairwise exchange rate correlations, explaining the heterogeneity that may be present across FX pairwise correlations and variables linked to the GFC.

3 Data and Econometric Approach

3.1 Data

This study uses daily exchange rate data for seven developed economies and seventeen emerging market countries, spanning September 3, 2004, to December 20, 2024. All exchange rates are quoted in local currency units per U.S. dollar (USD), and daily returns are computed as the first logarithmic differences of these exchange rates. Table 1 reports the descriptive statistics for the full sample. The results indicate that daily FX returns are generally skewed, with most series exhibiting high kurtosis and serial correlation. The Jarque-Bera (JB) test strongly rejects the null hypothesis of normality, a common finding in financial time series. All the series exhibit a high correlation for the squared returns, indicating the relevance of modeling the second moment of the series through the GARCH specifications.

As previously noted, we employ the VIX index as a daily proxy for the GFC. The VIX index assesses the market expectations of short-term volatility derived from options prices for the S&P 500 index. Policymakers and market participants use this indicator to assess global investors' sentiment, global risk appetite, and risk aversion. Additionally, as demonstrated in Miranda-Agrippino and Rey (2022) and Section 1, it exhibits a strong correlation with the GFC. An increasing VIX typically indicates heightened uncertainty and an elevated perception of risk within financial markets, whereas a decreasing VIX indicates more stable market conditions.

The sample used in our study includes significant episodes of global financial stress, as identified by spikes in the VIX index. The first significant surge in VIX occurred during the 2008 global financial crisis when it reached 80.86 on November 20, 2008. This spike was driven by the ongoing financial crisis amid severe liquidity stress by some major financial institutions. A second spike was observed on August 8, 2011, when the VIX rose to 48.00 following the U.S. credit rating downgrade and escalating concerns about the eurozone sovereign debt crisis.

Table 1: Descriptive statistics for the full sample

Exchange Rate returns	Mean	SD	Skewness	Kurtosis	JB	LB	LB2
EUR	−1.32E-17	0.554	−0.084	2.236	< 0.001	0.592	< 0.001
JPY	−7.91E-18	0.605	−0.248	6.304	< 0.001	0.042	< 0.001
GBP	−4.39E-17	0.572	0.222	3.071	< 0.001	0.019	< 0.001
CHF	4.14E-18	0.472	1.058	25.238	< 0.001	0.325	< 0.001
AUD	4.69E-17	0.772	0.344	9.930	< 0.001	0.006	< 0.001
NZD	1.10E-17	0.478	0.367	3.142	< 0.001	0.054	< 0.001
CAD	−9.47E-19	0.551	0.086	2.962	< 0.001	0.021	< 0.001
IDR	−6.03E-18	0.438	−0.029	21.116	< 0.001	0.247	< 0.001
INR	4.50E-18	0.399	0.273	8.059	< 0.001	0.105	< 0.001
KRW	1.15E-18	0.576	−1.164	57.340	< 0.001	< 0.001	< 0.001
PHP	−6.70E-18	0.335	0.073	2.713	< 0.001	0.034	< 0.001
SGD	7.10E-18	0.181	−0.037	6.566	< 0.001	< 0.001	< 0.001
THB	−2.73E-17	0.356	−0.065	7.789	< 0.001	0.177	< 0.001
TWD	−1.01E-17	0.196	0.020	2.740	< 0.001	< 0.001	< 0.001
CZK	−8.10E-17	0.713	0.083	3.452	< 0.001	0.312	< 0.001
HUF	−2.98E-18	0.333	−0.343	7.119	< 0.001	0.002	< 0.001
PLN	1.16E-17	0.844	0.194	4.365	< 0.001	0.120	< 0.001
TRY	3.73E-17	0.853	−1.174	89.778	< 0.001	< 0.001	< 0.001
ZAR	1.14E-17	1.016	0.285	2.500	< 0.001	0.614	< 0.001
BRL	1.87E-17	0.832	0.027	3.877	< 0.001	< 0.001	< 0.001
CLP	1.26E-17	0.727	0.067	4.976	< 0.001	< 0.001	< 0.001
MXN	−2.70E-17	0.596	0.684	8.005	< 0.001	0.132	< 0.001
COP	−5.51E-18	0.793	0.014	5.592	< 0.001	< 0.001	< 0.001
PEN	4.59E-18	0.322	−0.113	11.687	< 0.001	0.112	< 0.001

Source: Authors' computations. Exchange rate information is sourced from Bloomberg. The sample period spans from September 3, 2004, to December 20, 2024. JB represents the Jarque–Bera test. LB stands for Ljung–Box test over the returns, while LB2 does it for Ljung–box test on the squared returns. For all three tests, the p-values are presented. In this table, EUR stands for Euro, JPY for Yen, GBP for the British Pound, CHF for the Swiss Franc, AUD for the Australian Dollar, NZD for the New Zealand Dollar, CAD for Canadian Dollar, IDR for Indonesian Rupiah, INR for Indian Rupee, KRW for South Korean Won, PHP for Philippine Peso, SGD for Singapore Dollar, THB for Thai Bath, TWD for New Taiwan Dollar, CZK for Czech Koruna, HUF for Hungarian Forint, PLN for Polish Zloty, TRY for Turkish Lira, ZAR for South Africa Rand, BRL for Brazilian Real, CLP for Chilean Peso, MXN for Mexican Peso, COP for Colombian Peso and PEN for Peruvian Sol.

The COVID-19 pandemic in early 2020 triggered another historic peak, with the VIX hitting an intraday high of 82.69 on March 16, 2020, reflecting investor panic and global market turmoil. At the end of our sample, the Russian invasion of Ukraine in 2022 contributed to significant increases in the VIX. However, the subsequent spikes remained below the extreme levels of earlier crises. These instances serve as key reference points for identifying periods of global financial stress throughout the sample.

In addition, to compute the DCC-Copula models, we use several controls based on standard models of foreign exchange determination. We used short-term interest rate differentials, utilizing available money market rates and an exchange rate principal component, to assess foreign exchange appetite.[1] Descriptive statistics for these

[1]The FX principal component used in the exchange rate model for country i is based on Gamboa-Estrada and Romero (2022), and is computed as the common exchange rate factor derived from all analyzed exchange rates, excluding that of country i. This variable captures investors' appetite for the

variables are presented in Table 3 of the Appendix A.1. In addition, our panel exercises incorporate the daily returns of the U.S. Dollar Index (DXY)[2] and the S&P 500 to control global financial dynamics beyond those captured by the VIX.

3.2 Econometric Approach

Since we are interested in evaluating whether highly correlated currencies are more prone to be affected by the GFC, we use a two-step approach. First, we compute daily exchange rate correlations for an ample set of emerging and advanced economies using DCC-Copula models. This step enables us to obtain pairwise foreign exchange return correlations for the twenty-four exchange rates included in our sample.[3] Second, we used panel and quantile panel methods to evaluate whether the VIX index has a differentiated impact on these time-varying correlations. In this stage, we estimate a panel model using the previously obtained correlations, with the VIX index as the explanatory variable and the DXY and the S&P 500 daily returns as additional controls.

The DCC-Copula approach combines the multivariate DCC-GARCH and Copula methods to model the time-varying dependence structure. We begin by describing the DCC-GARCH, Copula, and DCC-Copula models, followed by a brief explanation of the panel model used in the second step of the econometric strategy.

3.3 DCC-GARCH model

Let $r_t = (r_{1,t}, \ldots, r_{N,t})'$ be the vector of returns for N exchange rates at time t, with the following conditional distribution:

$$r_t | \Omega_{t-1} \sim (0, H_t), \quad t = 1, \ldots, T, \tag{1}$$

where Ω_t denotes the information set up to time t, and $H_t = D_t R_t D_t$, with D_t as a diagonal matrix containing the time-conditional standard deviations and R_t as the conditional correlation matrix of the return series at time t.

analyzed currencies and reflects the comovement observed in the average levels of the exchange rates.

[2]The DXY, or U.S. Dollar Index, measures the value of the U.S. dollar relative to a basket of six major foreign currencies: the euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc. It is widely used by traders, policymakers, and economists to assess the strength of the dollar and its impact on global financial markets.

[3]Our sample includes FX rates for the European Union, Japan, United Kingdom, Switzerland, Australia, New Zealand, Canada, Indonesia, India, South Korea, Philippines, Singapore, Thailand, Taiwan, Czechia, Hungary, Poland, Turkey, South Africa, Brazil, Chile, Colombia, Mexico and Peru.

The Dynamic Conditional Correlation model (DCC), introduced by Engle (2002), describes the evolution of R_t. It assumes that the returns follow a univariate $ARMA(\tilde{p},\tilde{q}) - GARCH(p,q)$ process. Specifically:

$$r_{i,t} = \nu_i + \sum_{j=1}^{\tilde{p}} \tilde{\gamma}_{i,j} r_{i,t-j} + \sum_{j=1}^{\tilde{q}} \tilde{\lambda}_{i,j} \epsilon_{i,t-j} + \epsilon_{i,t} \tag{2}$$

$$\sigma^2_{i,t} = \omega_i + \sum_{j=1}^{p} \gamma_{i,j} \epsilon^2_{i,t-j} + \sum_{j=1}^{q} \lambda_{i,j} \sigma^2_{i,t-j}, \tag{3}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. The vector of standardized errors, ε_t, is defined as:

$$\varepsilon_t = D_t^{-1} \epsilon_t, \quad \varepsilon_t \sim (0, R_t), \tag{4}$$

with $\epsilon_t = (\epsilon_{1,t}, \ldots, \epsilon_{N,t})'$.[4]

Furthermore, the DCC-GARCH model assumes that the conditional correlation matrices of the standardized errors, Q_t, follow the dynamics given by: [5]

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1} \tag{5}$$

$$\bar{Q} = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_t \varepsilon'_t, \tag{6}$$

Where $\bar{Q}$ represents the unconditional variance matrix of the standardized errors.

The correlation matrix R_t is then defined as:

$$R_t = \left(Q_t^*\right)^{-1/2} Q_t \left(Q_t^*\right)^{-1/2},$$

where $Q_t^* = diag(Q_t)$, and the elements of R_t are given by: $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$, $i, j = 1, \ldots, N,\ t = 1, \ldots, T$, and $Q_t = [q_{ij,t}]_{i,j=1,\ldots,N}$.

Based on equations (2) to (6), the parameters of the DCC-GARCH model can be categorized into two groups. The first group consists of the parameters associated

[4] To estimate Equation (2), we incorporate two control variables: the interest rate differential between each economy and the United States, and a foreign exchange principal component, as detailed in Section 3.1.

[5] These equations correspond to a DCC(1,1) model. However, they can be easily extended to a more general DCC(p,q) specification.

with the univariate ARMA($\tilde{p}, \tilde{q}$)-GARCH(p, q) models. The second group includes the parameters governing the dynamics of the conditional correlation matrix R_t, namely α and β. Both sets of parameters can be estimated by maximizing the corresponding likelihood function.

The DCC-Copula model differs slightly from the DCC-GARCH model. However, before explaining its details, the following section provides a brief introduction to copulas.

3.4 Copula

A copula is a mathematical function that captures the dependence structure among multiple variables. According to Sklar's Theorem (1959),[6] any multivariate distribution of continuous random variables can be expressed in terms of a copula C, which links the joint distribution to its marginals. Formally, there exists a function $C : [0, 1]^N \rightarrow [0, 1]$ such that:

$$F\left(r_1, \ldots, r_N\right) = C\left(F_1\left(r_1\right), \ldots, F_N\left(r_N\right)\right), \tag{7}$$

where $F\left(r_1, \ldots, r_N\right)$ denotes the joint probability distribution function of N random variables $r_1, \ldots, r_N$, each with a corresponding marginal distribution $F_1\left(r_1\right), \ldots,$ $F_N\left(r_N\right)$.

For instance, the Gaussian Copula is defined as follows:

$$C(u_1, u_2, ..., u_N; R) = \Phi_R(\Phi^{-1}(u_1), ..., \Phi^{-1}(u_N)), \tag{8}$$

where $u_i = F_i(r_i)$ for $i = 1, \ldots, N$, $\Phi(.)$ represents the cumulative distribution function of a standard normal variable, and $\Phi_R(.)$ denotes the multivariate normal distribution function with correlation matrix R.

In practice, the joint distribution in equation (7) is evaluated using the standardized errors associated with the selected returns, as given in equation (4). Thus:

$$u_i = F_i(\varepsilon_i), \quad i = 1, \ldots, N. \tag{9}$$

[6] Described in Sklar (1959).

3.5 DCC-Copula model

Within the framework of a DCC-Copula model, the copula parameters associated with the correlation matrix change over time. Specifically, in the example given in equation (8), R_t replaces R to account for time variation. Here, the dynamics of R_t are governed by a DCC model,[7] as outlined below.

Thus, for the DCC-Gaussian Copula model, the following equations apply:

$$C(u_{1t}, u_{2t}, ..., u_{Nt}; R_t) = \Phi_{R_t}(\Phi^{-1}(u_{1t}), ..., \Phi^{-1}(u_{Nt})), \tag{10}$$

Moreover, the matrix R_t varies over time according to the dynamics of the DCC model:

$$\begin{aligned} R_t &= \left(Q_t^*\right)^{-1/2} Q_t \left(Q_t^*\right)^{-1/2}, \\ Q_t &= (1-\alpha-\beta)\bar{Q} + \alpha \xi_{t-1}\xi'_{t-1} + \beta Q_{t-1}, \\ \bar{Q} &= \frac{1}{T}\sum_{t=1}^{T} \xi_{t-1}\xi'_{t-1}, \end{aligned} \tag{11}$$

where $Q_t^* = diag(Q_t),\ \xi_t = (\xi_{1t}, .., \xi_{Nt})',\ \xi_{it} = \Phi^{-1}(u_{it}),\ i = 1, \ldots, N.$

It is important to note that DCC-Copula models require an elliptical copula, such as the Gaussian or t-Copula, as their parameters include the correlation matrix. Including these parameters is essential to this methodology, as they enable using the DCC approach.[8]

The parameters of the previous model are estimated by maximizing the following log-likelihood function:

$$l(R_t|u_1, ..., u_N) = \sum_{t=1}^{T} \ln\left(c(u_{1t}, ..., u_{Nt})\right), \tag{12}$$

where $c(\cdot)$ denotes the density function of the Copula. That is, $c(u_1, \ldots, u_N) = \frac{\partial^N C(u_1, \ldots, u_N)}{\partial u_1, \ldots, \partial u_N}$.

[7]Note that the DCC-GARCH model consists of two sets of equations. The first set includes the univariate equations (2) and (3), while the second set comprises the multivariate equations (5) and (6). In the DCC-Copula model, the univariate equations remain the same as in the DCC-GARCH model. However, the multivariate equations now incorporate copulas, as shown in (10) and (11).

[8]For a detailed review of elliptical copulas, see McNeil et al. (2015).

For a DCC-Gaussian Copula, the log-likelihood function is given by:

$$l(R_t|u_1, ..., u_N) = -\tfrac{1}{2} \sum_{t=1}^{T} \left[\log|R_t| + \xi_t' \, (R_t^{-1} - I_N \,) \, \xi_t \right] \tag{13}$$

where R_t is a function of α and β, as defined in equation (11).[9]

3.6 Panel model

Once the series of correlation matrices R_t is estimated using the DCC-Copula model, the second step of our methodology involves estimating a panel model. This model uses correlations as the dependent variable, while the VIX index acts as the main regressor. Given the heterogeneity observed in these correlations, we estimate the $\tau-$conditional quantile $Q_{y_{jt}}(\tau \mid VIX_t, z_{jt})$ for the following specification:

$$y_{jt} = \beta_{0,j} + \beta_1 VIX_t + \theta' z_{jt} + \nu_{jt}, \tag{14}$$

where y_{jt} corresponds to the correlation matrix R_t for $t = 1, \ldots, T$. It is important to note that R_t is a symmetric matrix of dimension $N \times N$, with all elements on the main diagonal equal to 1. Since we are only interested in the correlations between different pairs of exchange rate returns, we focus only on the upper triangular part of R_t. Thus, the index j for y_{jt} ranges from $j = 1, \ldots, \frac{N(N-1)}{2}$.

Furthermore, z_{jt} is a vector of control variables, including the daily returns of the S&P 500 and the U.S. Dollar Index (DXY), and ν_{it} represents the model's error term. Finally, β_0, β_1, and θ are the regression coefficients in the model.

Model (14) implies that

$$Q_{y_{jt}}(\tau \mid VIX_t, z_{jt}) = \beta_{0,j}(\tau) + \beta_1(\tau) VIX_t + \theta'(\tau) z_{jt}, \tag{15}$$

here, $Q_{y_{jt}}(\tau \mid VIX_t, z_{jt})$ denotes the $\tau-$conditional quantile of y_{jt} given the information from VIX_t and the control variables z_{jt}. The parameter $\beta_{0,j}(\tau)$ represents the intercept, $\beta_1(\tau)$ corresponds to the coefficient on VIX_t, and $\theta'(\tau)$ captures the effects of the control variables. All these coefficients depend on the quantile level τ.

The parameters of the panel quantile model described in (15) are estimated using the methodology proposed by Machado and Santos (2019).

[9] These results can be easily adapted for a DCC-t Copula by replacing equations (10) and (13) with the corresponding expressions for a t-Copula.

4 Results

In this section, we present the empirical results from the initial phase of our methodology, which employs the DCC-Copula model, followed by the second phase involving panel quantile regression analysis.

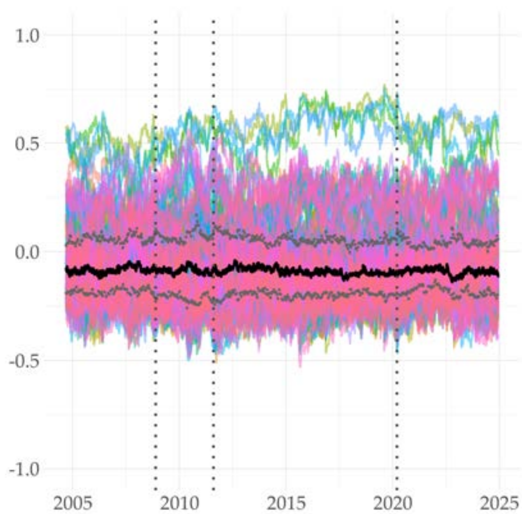
4.1 DCC-Copula model Correlation Results

In the DCC-Copula model, we use exchange rate returns for twenty-four economies, including the European Union, Japan, United Kingdom, Switzerland, Australia, New Zealand, Canada, Indonesia, India, South Korea, Philippines, Singapore, Thailand, Taiwan, Czechia, Hungary, Poland, Turkey, South Africa, Brazil, Chile, Colombia, Mexico and Peru. For control variables, we employ the difference between the economy's interest rate and the United States' interest rate, as well as the return of the currency common factor index, to characterize investors' appetite for the group to which each currency can be classified. In the second stage of the methodology, described in Section 3.6, which corresponds to the panel application, we incorporate the VIX index along with the control variables: the S&P 500 and the U.S. Dollar (DXY) daily returns. The analysis utilizes daily data spanning from September 2004 to December 2024. Returns are computed as the first differences of the natural logarithms of the series.

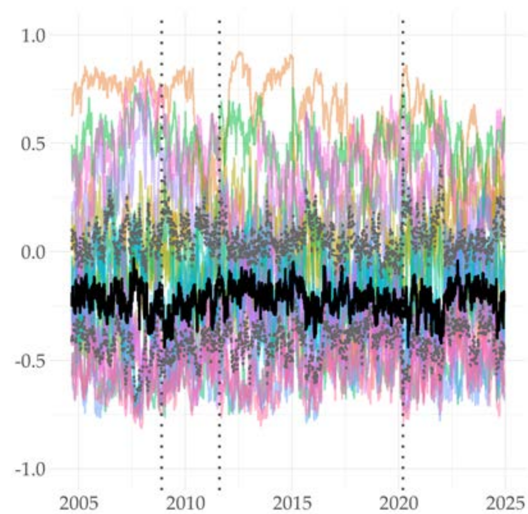
To estimate the DCC-Copula models, we used the following process. We first estimate univariate AR(p)-GARCH(1,1) models for the 24 return series. The lag lengths of the AR models were selected to minimize the Akaike Information Criterion (AIC).[10] Table 4 in Appendix A.2 shows diagnostic tests for the standardized residuals of these models. These results indicate that there is no evidence of autocorrelation in the first and second moments. After this, we estimate the univariate marginal distribution of the standardized residuals using the skew-t Student distribution proposed by Fernandez and Steel (1998) and apply the probability integral transform. Figure 5 in Appendix A.4 presents quantile-quantile plots comparing the empirical quantiles of the preceding series with those of a uniform reference distribution. The 45-degree lines suggest a good fit of these data. Finally, we estimate the parameters of the DCC-Copula model, as given in equations (10) and (11), using two elliptical copulas: the Gaussian and t copulas. The results of the test of Diks et al. (2010), that are presented in Table 5 in Appendix A.3, indicate that t Copula provides a better fit to the data.

[10] In the AR component of the model, we account for outliers in the data using dummy variables. A key outlier is associated with removing the EUR/CHF exchange rate floor on January 15, 2015. The effect of this event on the Swiss Franc is described in Auer et al. (2019), Auer et al. (2021), Oktay (2022), among others.

(a) Estimated Correlations for the 24 Economies



(b) Estimated Correlations for the 17 EM Economies



(c) Estimated Correlations for the 7 G10 Economies

Figure 2: Estimated Correlations of Exchange Rate Returns Using the DCC-Copula Model

Source: Authors' computations. Exchange rate information is sourced from Bloomberg. Each figure shows the estimated correlations using the DCC-Copula model. The top panel aggregates all 24 economies, while the bottom panels separate G10 and Emerging Markets.

Figure 2 presents the pairwise correlations over time across different country groups. The top panel (Figure 2(a)) shows results for the full sample of 24 currencies, while the two bottom panels display correlations among G10 advanced economies (Figure 2(c)) and Emerging Markets (Figure 2(b)), respectively. Each panel displays the median correlation (in black) and the first and third quartiles (in gray), providing a clearer representation of both the central tendency and the dispersion of correlations. Three vertical lines indicate key episodes of global financial stress: the Global Financial Crisis (November. 20, 2008), the U.S. debt ceiling and European sovereign crisis (August 8, 2011), and the COVID-19 shock (March 16, 2020). Overall, the broad range of correlations points to a significant degree of heterogeneity in exchange rate comovements.

Notably, the most strongly correlated currency pairs involve European and commodity-linked currencies, including EUR vs. CZK (0.88), EUR vs.PLN (0.81), CZK vs. PLN (0.81), and AUD vs. CAD (0.65), among others. This clustering is evident throughout the entire sample period, particularly among the G10 currencies. In contrast, the EMs panel exhibits lower overall dispersion but more episodic spikes in correlations. Emerging market currency pairs also display considerable heterogeneity, which may reflect varying degrees of exposure to global shocks, such as the GFC.

4.2 Assessing the relation between FX correlations and the GFC

The second step in our empirical strategy involves estimating the quantile panel models described in Section 3.6, following the approach proposed by Machado and Santos (2019). In these models, the correlations between exchange rate returns, obtained from the DCC-Copula model, serve as the dependent variable, while the VIX index is used as the main regressor. The S&P 500 and U.S. Dollar indices are included as control variables to account for other market factors that may influence FX correlations. The quantile panel approach is well-suited to this analysis, as the results in the previous section reveal substantial heterogeneity across pairwise foreign exchange (FX) correlations.

As a starting point, Table 2 reports the results of a panel regression in which the dependent variable is the pairwise correlation of exchange rate returns across 24 currencies, estimated using the DCC-Copula methodology.

Table 2: Results of the Panel Model

	Estimate	**SD**	**t-value**	**P-Value**
VIX	0.0171	0.0043	3.9507	< 0.0001
S&P 500	0.0338	0.0094	3.6125	0.0003
DXY	0.0293	0.0260	1.1294	0.2587
Observations	1459764			
F Statistic	160.7710	p-value: < 0.0001	(df = 3; 1459485)	

Source: Authors' computations. The dependent variable is the pairwise correlation of exchange rate returns for 24 economies, estimated using the DCC-Copula methodology. DXY denotes the U.S. Dollar Index. Robust standard errors are computed following the approach proposed by Driscoll and Kraay (1998). The regression includes cross-section fixed effects.

The results presented in Table 2 provide evidence of a significant positive association between global risk conditions and exchange rate comovement. The VIX index displays a positive and statistically significant coefficient, indicating that rising global financial stress is associated with higher correlations among exchange rates. Similarly, the S&P 500 index also shows a positive and significant coefficient, suggesting that improved global equity market performance tends to coincide with stronger exchange rate comovements, possibly reflecting shared global sentiment or capital flow dynamics. In contrast, the coefficient on the DXY index is not statistically significant. Overall, these findings underscore the role of global risk appetite and equity market performance in driving currency market synchronization.

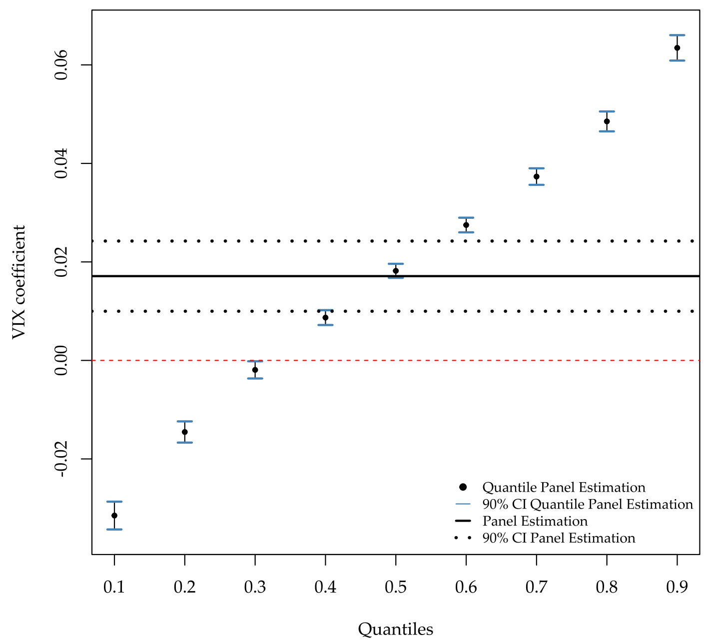


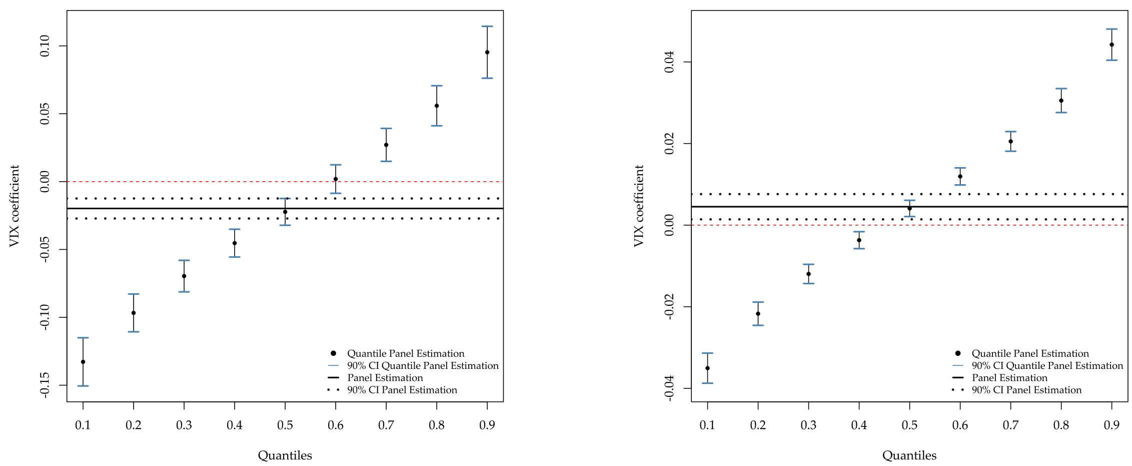
Figure 3: Quantile Panel Estimations of the VIX Coefficient

Source: Authors' computations. This graph displays the VIX coefficient for the Quantile Panel model. The coefficient corresponds to the panel described in Section 3.6, where the dependent variable is the pairwise correlation between exchange rate returns of twenty-four economies. The regressor is the VIX index, while the S&P 500 and U.S. Dollar indices serve as control variables. The X-axis represents the quantiles, with the solid circles indicating the estimated quantile coefficients. The short blue lines depict the 90% confidence interval for these estimates. The long horizontal line represents the panel coefficient estimator, while the long dotted lines show its 90% confidence interval. The quantile panel regression includes cross-section fixed effects.

As mentioned earlier, we estimate a quantile panel model to better assess the impact of the GFC on FX correlations. Following the previous exercise, the dependent variable is the pairwise correlation of exchange rate returns, estimated using the DCC-Copula methodology. Figure 3 presents the estimated VIX coefficients across different quantiles of the distribution of exchange rate return correlations.[11]

[11] Details of the quantile panel estimations are provided in Appendix A.5.

A key finding is that the impact of global financial risk, proxied by the VIX, is heterogeneous across the distribution of correlations. FX pairs with stronger baseline comovements tend to exhibit larger VIX coefficients, suggesting that during periods of heightened financial stress, these already closely linked currencies become even more synchronized. In contrast, FX pairs with low or negative correlations show smaller and less responsive VIX coefficients. This pattern suggests that the transmission of global financial conditions is uneven across currency pairs, and it is more pronounced among those with stronger inherent comovement.



(a) Quantile Panel Estimations for the 7 G10 Economies

(b) Quantile Panel Estimations for the 17 Emerging Market Economies

Figure 4: Quantile Panel Estimates of the VIX Coefficient for G10 and Emerging Market Economies.

Source: Authors' computations. This figure displays the estimated VIX coefficients across quantiles from the quantile panel model described in Section 3.6. The dependent variable is the pairwise correlation of exchange rate returns. The main regressor is the VIX index, while the S&P 500 and U.S. Dollar indices are included as control variables. Solid circles denote the estimated coefficients; short blue lines indicate 90% confidence intervals; and horizontal lines show the panel estimator along with its corresponding confidence band. Both models incorporate cross-sectional fixed effects.

Figure 4 presents the quantile panel estimates of the VIX coefficient for G10 (panel (a)) and EM (panel (b)) currency correlations. The horizontal axis represents the quantiles of the distribution of pairwise exchange rate correlations, while the vertical axis displays the estimated coefficients associated with the VIX index. Consistent with the results for the full sample, currency pairs with higher correlations exhibit greater sensitivity to the GFC, as indicated by larger VIX coefficients. In both graphs, these coefficients exceed the panel benchmark (shown by the solid black line) in the upper quantiles, confirming that the effect of the GFC is more pronounced among highly correlated currency pairs. The impact of the VIX is notably stronger for highly correlated G10 currency pairs than for their EM counterparts, highlighting a potentially differentiated transmission of global risk across advanced and emerging markets. These findings reinforce the heterogeneous nature of the GFC's transmission through FX markets. They are consistent with the broader pattern observed in Figure 3, in which the synchronization of closely linked currencies intensifies during periods of elevated global financial stress.

In synthesis, our quantile panel estimations reveal a heterogeneous and asymmetric transmission of the GFC to exchange rate correlations. While the baseline panel model confirms that the VIX positively and significantly influences FX comovements, the quantile approach uncovers a richer structure: the effect of the VIX is substantially stronger among highly correlated currency pairs. This relationship holds across the full sample as well as within the G10 and EM subsamples, although the magnitude of the effect is notably greater for G10 currencies. These findings suggest that the GFC intensified comovements primarily among currency pairs with pre-existing financial or structural linkages, pointing to a differentiated amplification mechanism during periods of global financial stress.

4.3 Robustness exercises

In the previous exercise, we analyzed the relationship between the VIX index, a proxy for the GFC, and the correlations of exchange rate returns for twenty-four economies. In this section, we estimate two robustness exercises.

First, we estimate the DCC-Copula and panel models without controlling for outliers in exchange rate returns. The panel estimation results for this case are presented in Table 9 in Appendix A.6. The results remain broadly consistent with our baseline findings (Table 2). The coefficient on the VIX remains positive and statistically significant, with a magnitude very close to the baseline estimate, indicating that extreme observations do not significantly affect the positive relationship between global financial risk and FX return correlations.

Second, we incorporate an alternative proxy for the GFC. Instead of the VIX index, we employ the Bloomberg Financial Condition Index (BFCIUS).[12] As shown in Figure 6 of Appendix A.7, both variables are highly correlated, with increases in the VIX index associated with tighter financial conditions. The quantile panel results using this proxy are presented in Tables 10, 11, 12 and 13 in Appendix A.6. This exercise shows that the BFICUS coefficient is positive and statistically significant, confirming that looser financial conditions are associated with higher correlations among exchange rate returns. The magnitude of the coefficient is economically meaningful and in line with the direction found in the baseline model (Table 2), suggesting that FX return

[12]The Bloomberg Financial Conditions Index is a daily index that market participants widely use to evaluate financial conditions. It measures the availability and cost of credit relative to the financial stress in the fixed-income, money, and equity markets. The index calculation considers credit spreads between treasury securities, municipals, commercial paper, and other lending rates.

correlations increase under tighter global financial conditions.[13]

The quantile panel estimates in Table 11 in Appendix A.6 further underscore the heterogeneity in the transmission of global financial conditions across the distribution of FX correlations. Notably, the sign of the BFICUS coefficient reverses across quantiles: it is negative and significant in the lower quantiles (i.e., for weakly or negatively correlated currency pairs). However, it turns positive and strongly significant in the upper quantiles (i.e., for strongly correlated pairs). This pattern aligns with our earlier findings using the VIX (Table 6 in Appendix A.5) and reinforces the idea that the influence of global financial conditions is asymmetric, amplifying comovement, particularly among FX pairs that are closely linked. The robustness of these results to the choice of GFC proxy reinforces our central conclusion: global financial conditions exert a significant yet uneven influence on the correlation structure of currency markets.

5 Concluding Remarks

Most of the literature on the impact of the GFC has focused on first moments, examining levels or changes in asset prices, capital flows, and credit growth. In contrast, this study investigates how the GFC may influence pairwise correlations among exchange rates. In this context, we offer three key findings. First, we document the time-varying nature of exchange rate correlations using a DCC-Copula model applied to a broad set of currencies. Second, we show that these correlations are significantly affected by global financial stress, as proxied by the VIX index. Third, we find that currency pairs exhibiting high correlation are especially sensitive to global risk fluctuations, suggesting that the GFC amplifies comovements among structurally linked currencies.

In our analysis, we exploit the heterogeneity in FX correlations using a quantile panel regression framework, which offers a more refined lens through which to examine the transmission of the GFC across currency markets. While the baseline panel model confirms a significant positive relationship between the VIX and exchange rate correlations, the quantile estimates reveal a more nuanced pattern: the effect of global financial stress is significantly stronger in the upper quantiles of the correlation distribution. This suggests that during periods of heightened global risk aversion—such as those linked to the GFC synchronized currencies, particularly among G10 economies, tend to become even more tightly linked. In contrast, currency pairs with historically low or negative correlations exhibit weaker or even inverse responses.

[13] The S&P 500 remains a significant predictor, whereas the DXY index continues to exhibit no statistically significant effect.

These findings point to a differentiated amplification mechanism, in which the transmission of the GFC is significant but uneven across currency pairs. Robustness checks support the credibility of our results. Controlling for outliers in exchange rate returns does not change the direction or significance of the key relationships. Moreover, replacing the VIX with the Bloomberg Financial Conditions Index (BFICUS) as an alternative proxy for global financial stress produces consistent outcomes, reaffirming that tighter financial conditions are associated with stronger FX correlations—particularly among currencies that are closely linked.

In sum, our findings contribute to the literature on international macroeconomics by providing new evidence on how the GFC shapes not only the levels but also the correlation structure of exchange rate returns. From a policy and investment perspective, these results carry important implications. Traditional foreign exchange diversification strategies may offer limited protection during episodes of global financial stress as currency comovements become more pronounced. Policymakers should also be mindful of the potential for synchronized FX movements to amplify external vulnerabilities during periods of turbulence. In this context, an area of further research should focus on the implications of the GFC on FX portfolio diversification and FX risk management and how the GFC affects higher moments of asset price returns and FX flows.

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A Appendix

A.1 Descriptive statistics

Table 3: Descriptive Statistics for the Regressor and Control Variables of the DCC-Copula and Quantile Panel models.

	Mean	SD	Skewness	Kurtosis	JB	LB	LB2
VIX Index	19.039	8.714	2.520	9.396	< 0.001	< 0.001	< 0.001
S&P 500 Index	0.032	1.182	−0.539	13.745	< 0.001	< 0.001	< 0.001
U.S. Dollar Index	0.003	0.468	−0.081	2.122	< 0.001	0.331	< 0.001
Interest rate differential							
d.EUR_diff	−0.0004	0.113	0.451	57.707	< 0.001	< 0.001	< 0.001
d.JPY_diff	−0.0005	0.068	−0.106	83.019	< 0.001	0.545	< 0.001
d.GBP_diff	−0.0007	0.141	−0.417	77.146	< 0.001	< 0.001	< 0.001
d.CHF_diff	−0.0005	0.133	0.046	38.282	< 0.001	< 0.001	< 0.001
d.AUD_diff	−0.0008	0.074	−1.263	68.426	< 0.001	0.010	< 0.001
d.NZD_diff	−0.0009	0.080	−2.897	89.933	< 0.001	0.181	< 0.001
d.CAD_diff	−0.0003	0.075	−0.088	65.995	< 0.001	0.016	< 0.001
d.IDR_diff	−0.0007	0.117	2.712	119.689	< 0.001	< 0.001	< 0.001
d.INR_diff	−0.0008	0.133	0.242	42.256	< 0.001	< 0.001	< 0.001
d.KRW_diff	−0.0007	0.071	−0.748	72.810	< 0.001	0.030	< 0.001
d.PHP_diff	−0.0009	0.109	0.213	83.489	< 0.001	0.591	< 0.001
d.SGD_diff	−0.0002	0.107	0.029	22.080	< 0.001	< 0.001	< 0.001
d.THB_diff	−0.0004	0.094	−12.561	709.735	< 0.001	0.156	0.410
d.TWD_diff	−0.0006	0.125	−0.546	69.845	< 0.001	< 0.001	< 0.001
d.CZK_diff	−0.0003	0.144	1.729	36.735	< 0.001	< 0.001	< 0.001
d.HUF_diff	−0.0014	0.109	6.999	226.659	< 0.001	0.389	0.176
d.PLN_diff	−0.0007	0.081	−0.110	59.869	< 0.001	0.006	< 0.001
d.TRY_diff	0.0030	2.867	−5.099	434.167	< 0.001	< 0.001	0.001
d.ZAR_diff	−0.0005	0.078	−0.503	58.814	< 0.001	0.037	< 0.001
d.BRL_diff	−0.0015	0.113	0.229	52.222	< 0.001	0.143	< 0.001
d.CLP_diff	0.0001	0.112	−2.014	112.110	< 0.001	< 0.001	0.003
d.MXN_diff	0.0001	0.091	−0.140	36.148	< 0.001	< 0.001	< 0.001
d.COP_diff	−0.0001	0.109	1.269	65.719	< 0.001	< 0.001	< 0.001
d.PEN_diff	−0.0006	0.108	−0.414	748.355	< 0.001	0.123	0.666
FX Principal Component							
PC_ALL_EX_EUR	0.003	0.166	0.236	3.469	< 0.001	< 0.001	< 0.001
PC_ALL_EX_JPY	0.003	0.166	0.198	3.381	< 0.001	< 0.001	< 0.001
PC_ALL_EX_GBP	0.003	0.166	0.260	3.669	< 0.001	< 0.001	< 0.001
PC_ALL_EX_CHF	0.003	0.166	0.210	3.272	< 0.001	< 0.001	< 0.001
PC_ALL_EX_AUD	0.003	0.166	0.271	3.556	< 0.001	< 0.001	< 0.001
PC_ALL_EX_NZD	0.003	0.166	0.173	3.177	< 0.001	< 0.001	< 0.001
PC_ALL_EX_CAD	0.003	0.166	0.188	3.208	< 0.001	< 0.001	< 0.001
PC_ALL_EX_IDR	0.003	0.166	0.230	3.380	< 0.001	< 0.001	< 0.001
PC_ALL_EX_INR	0.003	0.166	0.196	3.424	< 0.001	< 0.001	< 0.001
PC_ALL_EX_KRW	0.003	0.166	0.227	3.546	< 0.001	< 0.001	< 0.001
PC_ALL_EX_PHP	0.003	0.166	0.212	3.437	< 0.001	< 0.001	< 0.001
PC_ALL_EX_SGD	0.003	0.166	0.209	3.333	< 0.001	< 0.001	< 0.001
PC_ALL_EX_THB	0.003	0.166	0.234	3.652	< 0.001	< 0.001	< 0.001
PC_ALL_EX_TWD	0.003	0.166	0.186	3.232	< 0.001	< 0.001	< 0.001
PC_ALL_EX_CZK	0.003	0.166	0.194	3.411	< 0.001	< 0.001	< 0.001
PC_ALL_EX_HUF	0.003	0.166	0.213	3.434	< 0.001	< 0.001	< 0.001
PC_ALL_EX_PLN	0.003	0.166	0.202	3.383	< 0.001	< 0.001	< 0.001
PC_ALL_EX_TRY	0.003	0.166	0.210	3.476	< 0.001	< 0.001	< 0.001
PC_ALL_EX_ZAR	0.003	0.166	0.205	3.383	< 0.001	< 0.001	< 0.001
PC_ALL_EX_BRL	0.003	0.166	0.217	3.193	< 0.001	< 0.001	< 0.001
PC_ALL_EX_CLP	0.003	0.166	0.254	3.626	< 0.001	< 0.001	< 0.001
PC_ALL_EX_MXN	0.003	0.166	0.196	3.295	< 0.001	< 0.001	< 0.001
PC_ALL_EX_COP	0.003	0.166	0.193	3.392	< 0.001	< 0.001	< 0.001
PC_ALL_EX_PEN	0.003	0.166	0.219	3.413	< 0.001	< 0.001	< 0.001

Source: Authors' computations. All time series data is obtained from Bloomberg. The sample period spans from September 3, 2004, to December 20, 2024. JB represents the Jarque–Bera test. LB stands for Ljung–Box test over the returns, while LB2 does it for the Ljung–Box test on the squared returns. For all three tests, the p-values are presented. In this table, EUR stands for Euro, JPY for Yen, GBP for the British Pound, CHF for the Swiss Franc, AUD for the Australian Dollar, NZD for the New Zealand Dollar, CAD for Canadian Dollar, IDR for Indonesian Rupiah, INR for Indian Rupee, KRW for South Korean Won, PHP for Philippine Peso, SGD for Singapore Dollar, THB for Thai Bath, TWD for New Taiwan Dollar, CZK for Czech Koruna, HUF for Hungarian Forint, PLN for Polish Zloty, TRY for Turkish Lira, ZAR for South Africa Rand, BRL for Brazilian Real, CLP for Chilean Peso, MXN for Mexican Peso, COP for Colombian Peso and PEN for Peruvian Sol. The FX principal component, PC_ALL_EX_i, for country i, is based on Gamboa-Estrada and Romero (2022), and is computed as the common exchange rate factor derived from all analyzed exchange rates, excluding that of country i. This variable captures investors' appetite for the analyzed currencies and also reflects the comovement observed in the average levels of the exchange rates. The interest rate differential is defined as the difference between short-term interest rates and the U.S. Federal Funds rate.

A.2 Residual diagnostics

Table 4: Multivariate Specification Test for the Standardized Residuals

	Lags	**Statistic**	**P-Value**
Portmanteau	500	284238.7	0.99
Portmanteau (squared residuals)	500	282281.2	0.99

Source: Authors' computations. Ljung-Box test for the standardized residuals and the squared standardized residuals. The null hypotheses indicates that there is no autocorrelation.

A.3 Copula Selection

Table 5: Copula Selection

Klic	P-Value
857.812	< 0.001

Source: Authors' computations. Test of Diks et al. (2010). The null hypotheses indicates a there is no difference between a Gaussian and a t Copula, while the alternative indicates a t Copula.

A.4 QQ-plot of pseudo-sample

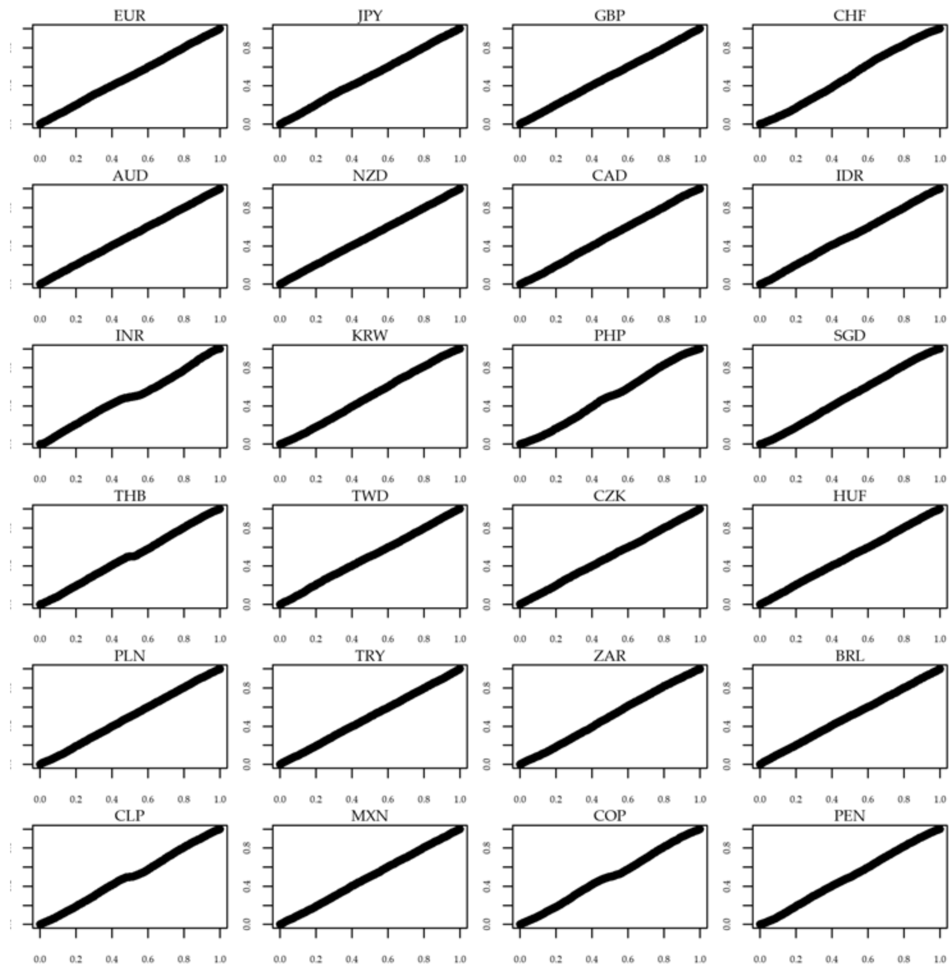

Figure 5: QQ-plot of Pseudo-samples Used in the Copula of the DCC-Copula Model.

Source: Authors' computations. QQ-plot of $\hat{F}(\hat{\varepsilon}_i)$ against a uniform reference distribution. $\hat{\varepsilon}_i$ corresponds to the standardized residuals for each of the 24 series that are considered and $\hat{F}(x)$ is the skew t-student distribution of x. Additionally, EUR stands for Euro, JPY for Yen, GBP for British Pound, CHF for Swiss Franc, AUD for Australian Dollar, NZD for New Zealand Dollar, CAD for Canadian Dollar, IDR for Indonesian Rupiah, INR for Indian Rupee, KRW for South Korean Won, PHP for Philippine Peso, SGD for Singapore Dollar, THB for Thai Bath, TWD for New Taiwan Dollar, CZK for Czech Koruna, HUF for Hungarian Forint, PLN for Polish Zloty, TRY for Turkish Lira, ZAR for South Africa Rand, BRL for Brazilian Real, CLP for Chilean Peso, MXN for Mexican Peso, COP for Colombian Peso, and PEN for Peruvian Sol.

A.5 Results of the Quantile Panel Model

Table 6: Quantile Panel Estimations of the VIX Coefficient

Quantile	VIX coefficient	SD	Z-stat	P-Value
0.1	−0.0315	0.0017	−18.3641	< 0.0001
0.2	−0.0145	0.0013	−11.0951	< 0.0001
0.3	−0.0019	0.0011	−1.8100	0.0701
0.4	0.0087	0.0009	9.4877	< 0.0001
0.5	0.0182	0.0009	20.9969	< 0.0001
0.6	0.0275	0.0009	30.4750	< 0.0001
0.7	0.0373	0.0010	36.5566	< 0.0001
0.8	0.0485	0.0012	39.5426	< 0.0001
0.9	0.0635	0.0016	40.4580	< 0.0001

Source: Authors' computations. Estimation results of the quantile panel model using the methodology proposed by Machado and Santos (2019). The dependent variable of the model corresponds to the correlations of exchange rate returns of 24 economies, estimated with the DCC-Copula methodology. This model includes VIX index as the regressor. Additionally, the S&P 500 and DXY indices are used as control variables.

Table 7: Quantile Panel Estimations of the S&P 500 Coefficient

Quantile	S&P 500 coeff.	SD	Z-stat	P-Value
0.1	−0.0235	0.0126	−1.8596	0.0629
0.2	−0.0035	0.0096	−0.3606	0.7184
0.3	0.0114	0.0078	1.4603	0.1442
0.4	0.0239	0.0067	3.5468	< 0.0001
0.5	0.0351	0.0064	5.5097	< 0.0001
0.6	0.0460	0.0066	6.9443	< 0.0001
0.7	0.0576	0.0075	7.6769	< 0.0001
0.8	0.0708	0.0090	7.8466	< 0.0001
0.9	0.0884	0.0115	7.6616	< 0.0001

Source: Authors' computations. Estimation results of the quantile panel model using the methodology proposed by Machado and Santos (2019). The dependent variable of the model corresponds to the correlations of exchange rate returns of 24 economies, estimated with the DCC-Copula methodology. This model includes VIX index as the regressor. Additionally, the S&P 500 and DXY indices are used as control variables.

Table 8: Quantile Panel Estimations of the U.S. Dollar Coefficient (DXY)

Quantile	U.S. Dollar coeff.	SD	Z-stat	P-Value
0.1	0.0655	0.0300	2.1838	0.0290
0.2	0.0529	0.0229	2.3098	0.0209
0.3	0.0435	0.0185	2.3471	0.0189
0.4	0.0356	0.0160	2.2231	0.0262
0.5	0.0285	0.0151	1.8858	0.0593
0.6	0.0216	0.0158	1.3723	0.1700
0.7	0.0143	0.0178	0.8020	0.4226
0.8	0.0060	0.0214	0.2786	0.7805
0.9	−0.0051	0.0274	−0.1868	0.8518

Source: Authors' computations. Estimation results of the quantile panel model using the methodology proposed by Machado and Santos (2019). The dependent variable of the model corresponds to the correlations of exchange rate returns of 24 economies, estimated with the DCC-Copula methodology. This model includes VIX index as the regressor. Additionally, the S&P 500 and DXY indices are used as control variables.

A.6 Robustness of the Panel Model Estimations

Table 9: Results of the Panel Model Without Controlling for Outliers

	Estimate	SD	t-value	P-Value
VIX	0.0167	0.0044	3.7727	0.0002
S&P 500	0.0334	0.0095	3.5137	0.0004
DXY	0.0286	0.0262	1.0939	0.2741
Observations	1459764			
F Statistic	152.7830	p-value: < 0.0001	(df = 3; 1459485)	

Source: Authors' computations. The dependent variable is the pairwise correlation of exchange rate returns for 24 economies, estimated using the DCC-Copula methodology. DXY denotes the U.S. Dollar Index. Robust standard errors are computed following the approach proposed by Driscoll and Kraay (1998). The regression includes cross-section fixed effects.

Table 10: Panel Model Results with the BFICUS Index as Regressor Variable.

	Estimate	SD	t-value	P-Value
BFICUS	0.0535	0.0234	2.2901	0.0221
S&P 500	0.0211	0.0087	2.4226	0.0154
DXY	0.0330	0.0261	1.2624	0.2069
Observations	1459764			
F Statistic	56.5252	p-value: < 0.0001	(df = 3; 1459485)	

Source: Authors' computations. Estimation results from the panel model using the Bloomberg Financial Conditions Index (BFCIUS) as the main regressor instead of the VIX. The dependent variable is the pairwise correlation of exchange rate returns for 24 economies, estimated using the DCC-Copula methodology. DXY denotes the U.S. Dollar Index. Robust standard errors are computed following the approach proposed by Driscoll and Kraay (1998). The regression includes cross-section fixed effects.

Table 11: Quantile Panel Estimations of the BFICUS Coefficient

Quantile	BFICUS coefficient	SD	Z-stat	P-Value
0.1	−0.3056	0.0097	−31.6087	< 0.0001
0.2	−0.1805	0.0074	−24.4327	< 0.0001
0.3	−0.0871	0.0060	−14.5609	< 0.0001
0.4	−0.0087	0.0052	−1.6760	0.0937
0.5	0.0616	0.0049	12.6276	< 0.0001
0.6	0.1306	0.0051	25.7238	< 0.0001
0.7	0.2030	0.0057	35.3552	< 0.0001
0.8	0.2849	0.0069	41.3700	< 0.0001
0.9	0.3952	0.0088	44.8853	< 0.0001

Source: Authors' computations. Estimation results of the quantile panel model using the methodology proposed by Machado and Santos (2019). The dependent variable of the model corresponds to the correlations of exchange rate returns of 24 economies, estimated with the DCC-Copula methodology. This model includes BFICUS index as the regressor. Additionally, the S&P 500 and DXY indices are used as control variables.

Table 12: Quantile Panel Estimations of the S&P 500 Coefficient

Quantile	S&P 500 coefficient	SD	Z-stat	P-Value
0.1	−0.0176	0.0126	−1.4017	0.1601
0.2	−0.0042	0.0096	−0.4329	0.6651
0.3	0.0060	0.0078	0.7609	0.4467
0.4	0.0144	0.0067	2.1408	0.0323
0.5	0.0220	0.0063	3.4626	0.0005
0.6	0.0294	0.0066	4.4540	< 0.0001
0.7	0.0372	0.0075	4.9809	< 0.0001
0.8	0.0460	0.0090	5.1348	< 0.0001
0.9	0.0579	0.0115	5.0513	< 0.0001

Source: Authors' computations. Estimation results of the quantile panel model using the methodology proposed by Machado and Santos (2019). The dependent variable of the model corresponds to the correlations of exchange rate returns of 24 economies, estimated with the DCC-Copula methodology. This model includes BFICUS index as the regressor. Additionally, the S&P 500 and DXY indices are used as control variables.

Table 13: Quantile Panel Estimations of the U.S. Dollar (DXY) Coefficient

Quantile	U.S. Dollar coefficient	SD	Z-stat	P-Value
0.1	0.0569	0.0300	1.9001	0.0574
0.2	0.0486	0.0229	2.1235	0.0337
0.3	0.0424	0.0185	2.2892	0.0221
0.4	0.0371	0.0160	2.3240	0.0201
0.5	0.0325	0.0151	2.1511	0.0315
0.6	0.0279	0.0157	1.7734	0.0762
0.7	0.0230	0.0178	1.2951	0.1953
0.8	0.0176	0.0213	0.8228	0.4106
0.9	0.0102	0.0273	0.3739	0.7085

Source: Authors' computations. Estimation results of the quantile panel model using the methodology proposed by Machado and Santos (2019). The dependent variable of the model corresponds to the correlations of exchange rate returns of 24 economies, estimated with the DCC-Copula methodology. This model includes BFICUS index as the regressor. Additionally, the S&P 500 and DXY indices are used as control variables.

A.7 VIX and BFICUS indices

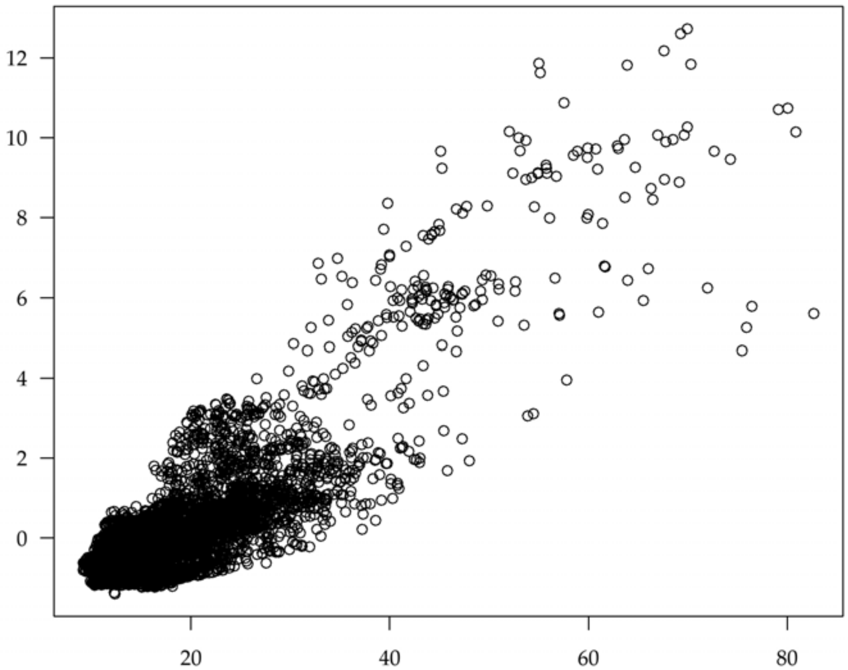

Figure 6: VIX index vs. BFICUS index

Source: The time series data is obtained from Bloomberg and authors' computations. The scale of the VIX index is shown on the X-axis, while the scale of the Bloomberg Financial Conditions Index (BFICUS) is indicated on the Y-axis. The BFICUS index is scaled such that increases in the index indicate a deterioration in financial conditions.