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An empirical evaluation of transitory and permanent components of the exchange rate volatility

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ABSTRACT

We analyse the volatility behaviour of major currency rates, using daily spot exchange rate data for sixteen different currencies relative to the US from 1999 to 2023. We apply the component-GARCH model proposed by Engle and Lee (1999) to break down volatility into permanent and transitory components. In addition, we apply a correlation analysis between permanent and transitory volatilities to examine their statistical association, disentangle their mutual influence, principal components analysis of long-run and short-run volatility; and identify clusters among them. Results suggest that (i) permanent and transitory volatility components capture the most relevant events of the turbulent 21st century, showing higher volatility persistence with long memory in the permanent component than in the transitory one; (ii) cross-country correlations are lower for the transitory component than the permanent component and principal component analysis reveals a long-run volatility trend; (iii) there exists a big group of currencies with similar traits in the permanent and transitory components of volatility; and (iv) the transitory component is closely associated with measures of market sentiment and financial tensions. Therefore, this study provides important insights into the behaviour of various components of exchange rate volatility, highlighting key aspects that have not been sufficiently explored.

KEYWORDS

Conditional variance; component model; cluster analysis; exchange rates

JEL CLASSIFICATION

C32; F33; G12

I. Introduction

Global exchange rate volatility has been decreasing over the twenty-first century, notably after 2014 (Ilzetzki, Reinhart, and Rogoff 2020). However, the concurrent crises and turmoil experienced to date have caused significant swings in the foreign exchange market, reflecting broader and faster movements in bilateral primary rates than previous events since the 1970s, as financial markets worldwide have become much more integrated. In this respect, although since the global financial crisis of 2008 (GFC), considerable emphasis has been paid to the spread of systematic risk across different financial market segments, the phenomenon of risk propagation among currencies has been studied to a relatively lesser extent.

Volatile financial markets are a symptom of general uncertainty about the immediate and long-term future. Exchange rate volatility is particularly notable within financial series, as it significantly impacts international trade, investment, monetary policy, and overall macroeconomic stability. Besides, international trade and investment decisions are more challenging when exchange rates are volatile because volatility raises exchange rate risk. The expected rates of return on international investments may vary due to volatile currency rates negatively affecting the efficient international allocation of resources. If exchange rate stabilization is to be accomplished, locating the cause of variations is crucial. In this sense, measuring and discerning the relative relevance of the permanent and transitory (P-T) components of exchange rate volatility can be useful. Furthermore, Ndou, Gumata, and Ncube (2017) highlight that the aggregation of exchange rate volatility shocks may conceal the distinct impacts of P-T volatility components on the macroeconomy.

In previous literature on exchange rate volatility, several studies have examined the relationship between the volatility of various currencies and the volatility of financial and macroeconomic variables (Ilzetzki, Reinhart, and Rogoff 2019, 2020; Rogoff 2006). Recently, Stavrakeva and Tang

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(2024) analysed the connections between the volatility of both *realised* and *expected* macroeconomic variables and exchange rate volatility. They explored the time-varying volatility of seven currencies and discovered significant heterogeneity in the trends of exchange rate volatility. Additionally, other recent papers (see, e.g. Asadi et al. 2023; Fernández-Rodríguez and Sosvilla-Rivero 2020; Suleman, Tabash, and Sheikh 2022; Tabash, Asad, et al. 2022; Tabash, Babar, et al. 2022; Tabash, Sheikh, Asad, et al. 2023; Tabash, Sheikh, Matar, et al. 2023) have primarily focused on the relationships between stock markets, oil prices, and exchange rate volatility.

However, the existing literature on the volatility of P-T components is relatively limited. S.-W. Chen and Shen (2004) utilized a component-GARCH-jump model to identify 172 jumps in Taiwan's exchange rate from January 1988 to March 2003. They found that the Asian financial crisis in 1997 caused not only temporary volatility effects but also permanent ones. Ndou, Gumata, and Ncube (2017) analysed the impact of exchange rate volatility on macroeconomic variables – such as manufacturing production growth, inflation rates, and the repo rate – in South Africa from 1990 to December 2014. Their findings suggest that overall volatility contributes to more significant fluctuations in output growth than the volatility of P-T components.

Against this backdrop, this paper aims to provide a comprehensive analysis of the volatility behaviour of major exchange rates to address existing research gaps. Our essential contribution to the existing literature is an empirical evaluation of the permanent (long-run) and transitory (short-run) components of exchange rate volatility. To the best of our knowledge, no study analyses these long-run and short-run components of volatility and explores their behaviour. Two main arguments support the importance of obtaining the P-T components of volatility. First, we do not know whether permanent or transitory volatility initially drives overall volatility or plays a significant role later in the volatility episode. Second, it remains unclear whether permanent volatility will continue over time and which shocks contribute to this persistence (Ndou, Gumata, and Ncube 2017). Additionally, policymakers can benefit from the insights gained about the P-T components, as this information will help them respond effectively and determine the most appropriate economic policy measures to implement.

This paper specifically aims to address several important questions: (a) is it possible to associate changes in volatility with the most relevant events of this turbulent 21st century? How persistent are the P-T components of volatility?; (b) are the permanent and transitory components of the currencies linked?; (c) is it possible to find similar traits for the currencies under study?; (d) is the detected transitory volatility component related to market sentiment and financial tensions? To that end, we use daily data on spot exchange rates of 16 currencies against the United States, covering 188.1% of the average daily turnover during the 1999–2023 period. Our analysis follows four steps. Firstly, we decompose volatility in permanent and transitory using the component-GARCH model developed by Engle and Lee (1999). Secondly, we apply a correlation analysis between permanent and transitory volatilities to examine their statistical association and disentangle their mutual influence. Moreover, we apply principal component analysis to complement the correlation analysis and explore the existence or absence of common volatility trends. Thirdly, we look for clusters among the long-run and short-run components. Finally, we investigate the potential drivers of the transitory volatility component we have detected.

Understanding the dynamics of foreign exchange market volatility transmission is crucial for effective portfolio management and significantly impacts currency hedging strategies (Jayasinghe and Tsui 2008; Kočenda and Moravcová 2023). A quantitative evaluation of these issues is needed, strongly motivating our in-depth examination.

The paper is organized as follows. Section II describes the econometric methodology adopted in this study. Section III presents the data and the empirical result, and Section IV offers some concluding remarks. An online Supplementary Appendix provides detailed analyses.

II. Econometric methodology

Decomposing time-varying volatility into permanent and transitory components

Engle and Lee (1999) proposed a 'component-GARCH' (C-GARCH) model that offers several significant advantages for analysing financial volatility: i) its ability to separate volatility into permanent (long-run) and transitory (short-run) components, ii) better fit for financial data as the GARCH component model captures the heteroskedastic conditional volatility often present in financial markets, iii) more accurate predictions about future price behaviour and volatility in financial markets, iv) its applicability in risk management by improving our understanding the sources of volatility, and v) its great flexibility to model and analyse financial time series with complex volatility behaviours, an essential feature in a financial environment that is often marked by high volatility events or unexpected structural changes.

Distinguishing between permanent and transitory volatility enhances our understanding of uncertainty sources, which is essential as investment decisions primarily rely on whether this uncertainty is permanent or transitory (Byrne and Davis 2005).

Consider the original GARCH model:

$$\sigma_t^2 = \omega + \alpha(\varepsilon_{t-1}^2 - \omega) + \beta(\sigma_{t-1}^2 - \omega) \tag{1}$$

As can be seen, the conditional variance of the returns here has mean reversion to some time-invariable value, ω. The influence of a past shock eventually decays to zero as the volatility converges to this value ω according to the powers of (α+β). The standard GARCH model therefore makes no distinction between the long-run and short-run decay behaviour of volatility persistence.

For the permanent specification, the C-GARCH model replaces the time-invariable mean reversion value, ω, of the original GARCH formulation in Equation (1) with a time variable component q_t:

$$q_t = \hat{\omega} + \rho(q_{t-1} - \hat{\omega}) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{2}$$

where, q_t is the long-run time-variable volatility level, which converges to the long-run time-invariable volatility level $\hat{\omega}$ according to the magnitude of ρ. This permanent component thus describes the long-run persistence behaviour of the variance and is associated with long-term structural changes in the market. The long-run time-invariable volatility level $\hat{\omega}$ can be viewed as the long-run level of returns variance for the relevant sector when past errors no longer influence future variance in any way. Stated differently, the value $\hat{\omega}$ can be seen as a measure of the 'underlying' level of variance for the respective series. The closer the estimated value of the ρ in Equation (2) is to one the slower q_t approaches $\hat{\omega}$, and the closer it is to zero the faster it approaches $\hat{\omega}$. The value ρ therefore provides a measure of the long-run persistence.

The second part of C-GARCH model is the specification for the short-run dynamics, the behaviour of the volatility persistence around this long-run time-variable mean, q_t:

$$\sigma_t^2 - q_t = \gamma(\varepsilon_{t-1}^2 - q_{t-1}) + \lambda(\sigma_{t-1}^2 - q_{t-1}) \tag{3}$$

According to this transitory specification, the deviation of the current condition variance from the long-run variance mean at time t ($\sigma_t^2 - q_t$) is affected by the deviation of the previous error from the long-run mean ($\varepsilon_{t-1}^2 - q_{t-1}$) and the previous deviation of the condition variance from the long-run mean ($\sigma_{t-1}^2 - q_{t-1}$). Therefore, in keeping with its GARCH theoretical background, the C-GARCH specification continues to take account of the persistence of volatility clustering by having the conditional variance as a function of past errors. As the transitory component describes the relationship between the short-run and long-run influence decline rates of past shocks values of (γ+λ) closer to one imply slower convergence of the short-run and long-run influence decline rates, and values closer to zero the opposite, reflecting temporary shocks that affect prices only in the short term. The value (γ+λ) is therefore a measure of how long this short-run influence decline rate is.

Together, these two components of the C-GARCH model describe, just like the original GARCH formulation, how the influence of a past shock on future volatility declines over time. With the C-GARCH model however, this persistence is separated into a short-run and long-run component, along with the estimation of the underlying variance level once the effect of both components has been removed from a series.

The two volatility components are typically seen as being driven by distinct sources. The permanent volatility component is often interpreted as representing shocks to economic fundamentals, while the transitory volatility component is seen to be driven by market sentiment and short-term position-taking (see, e.g. Chou 2017).

Cluster analysis

We search for clusters in the permanent and cyclical volatilities of exchange rates to investigate the potential of groups of currencies in our sample. Cluster analysis organizes currencies with similar traits using only information derived from the data. The intention is for currencies in a group to be similar to one another and distinct from those in other groupings. The more similarities within a group (lower intra-cluster distances) and the greater the disparities between groups (higher inter-cluster distances), the more distinct the clustering. The partitioning and hierarchical algorithms have both been utilized as clustering techniques. The first algorithm begins by creating groups for each nation. The countries are categorized using a resemblance criterion at various degrees. The process is repeated until every nation is in a single cluster. The clustering sequence is shown in a standard plot called a tree diagram, allowing us to view the entire process. The number of clusters (m) present in our set of permanent or cyclical volatility components can be inferred from this diagram.

The next stage is to use the partitioning clustering technique known as k-means,[1] a non-hierarchical, unsupervised data mining that separates data into one or more groups or clusters. The goal is to form groupings in which the data points in one cluster are comparable to each other while the data points in other clusters are less similar. Each currency under study is assigned to a particular cluster via k-means clustering, providing a single cluster level. Additionally, this method clusters vast volumes of data, such as temporal series, because it uses the individuals' actual observations rather than their proximity to one another. The algorithm finds a partition in which countries within each cluster are as close to each other as possible and as far from the countries in other clusters as possible. k-means clustering minimizes the sum of square Euclidean distances between a cluster centre or centroid and all the points within the cluster. However the initial random assignment determines the outcome. In order to get around the k-means method's two drawbacks – the selection of the number of clusters and the results' dependence on the initial partition – we repeated the algorithm for a different randomly chosen set of initial centroids and chose the local minimum that produced the silhouette plots that show how closely spaced apart each point in one cluster is from a point in its neighbouring clusters. Using this method, which, due to its effectiveness and ease of use, can be applied in various fields, we can assess the robustness of the number of chosen clusters.

III. Data and empirical results

Data

We use daily data of spot exchange rates of 16 currencies against the United States dollar from 4 January 1999 to 6 January 2023 from the Federal Reserve Bank of St. Louis. The currencies are the Australian dollar (AUD), the Brazilian real (BRL), the Canadian dollar (CAD), the Swiss franc (CHF), the Chinese yuan (CNY), the European euro (EUR), the United Kingdom pound sterling (GBP), the Indian rupee (INR), the Japanese yen (JPY), the South Korean won (KRW), the Mexican peso (MXN), the Norwegian krone (NOK), the New Zealand dollar (NZD), the Swedish krone (SEK), the Singapore dollar (SGD) and the South African rand (ZAR). These currencies cover 188.1% of the average daily turnover (BIS 2022).[2]

Figure 1 plots the log differences of daily spot exchange rates for each country in our sample. These figures indicate remarkable volatility differences along the sample size under analysis.

Empirical results

Step 1: permanent and transitory components

The empirical analysis developed in this subsection tries to shed some light on two relevant questions: Is it possible to associate changes in volatility with the most relevant events of this turbulent 21st

[1]The k-means approach was independently created by Sebestyen (1962) and MacQueen (1967) as a way of looking for the best partitions. k-means has gained much popularity since this discovery, and it is now widely used in cluster analysis (Gordon and Henderson 1977) and pattern recognition (Duda, Hart, and Stork 2001), among other fields.

[2]Because two currencies are involved in each transaction, the sum of the percentage shares of individual currencies totals 200% instead of 100%.

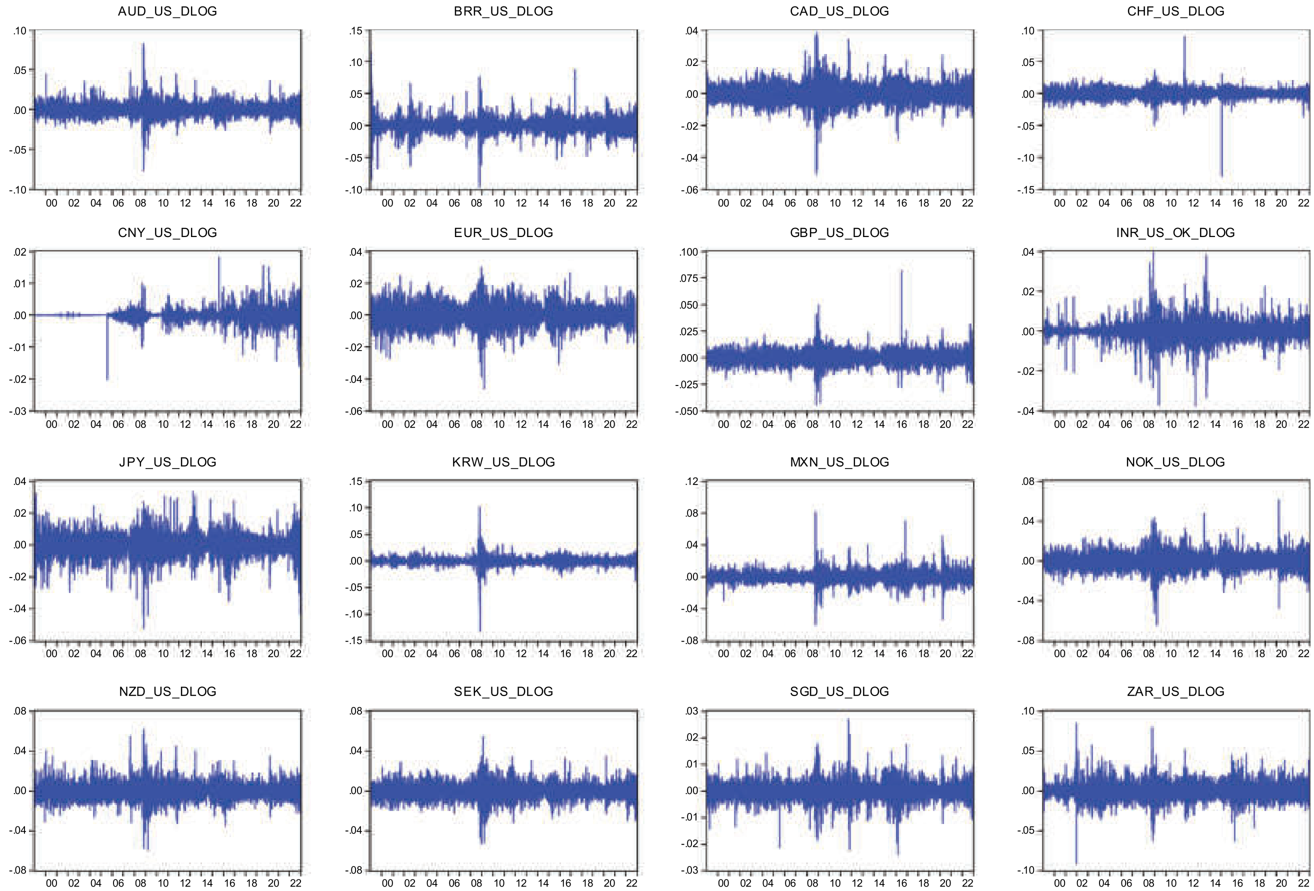

Figure 1. Daily rate of change of spot exchange rates.

century? And how persistent are the P-T components of volatility?

Figure 2 illustrates daily spot exchange rates' total, permanent and transitory variance. From this figure, we could extract several initial regularities. Firstly, we observe that the long-run component of volatility is much higher than the short-run component for all currencies. Secondly, the permanent and transitory volatility components capture the most relevant events of this turbulent 21st century. Table 1 summarizes the regularities experienced in the permanent and transitory volatility during the main events registered during the sample. The 11 September 2001 attacks moderately affected BRR, EUR, JPY, NZD, SEK, SGD and ZAR currencies volatility. In contrast, the 2008 GFC substantially impacted the volatility of all currencies, showing strong peaks in the permanent volatility component. Overall, the European sovereign debt crisis affected European currencies such as EUR, GBP and NOK. The 2017 Brexit referendum affected several currencies, generating a sharp spike in volatility in the pound sterling. Almost all the currencies under examination show moderate and small volatility spikes capturing another relevant event: the COVID-19 pandemic and the subsequent Great Lockdown. Finally, a positive trend in volatility is observed at the very end of the sample, reflecting the initial effects of the conflict between Ukraine and Russia on the volatility of almost all currencies.

The first columns of Table 2 exhibit the numerical estimation results obtained from the C-GARCH model using the parametric Maximum Likelihood Estimation (MLE) estimation method. As we can observe in columns 2 to 4 in Table 2, all the estimated coefficients $(\hat{\omega}, \hat{\rho}, \hat{\varphi})$ are significant for the permanent component at the 1% level for all currencies except for the EUR. In particular: a) the estimated long-run average volatility $(\hat{\omega})$ is positive, small in magnitude, but significant at the 1% level in all cases; b) the

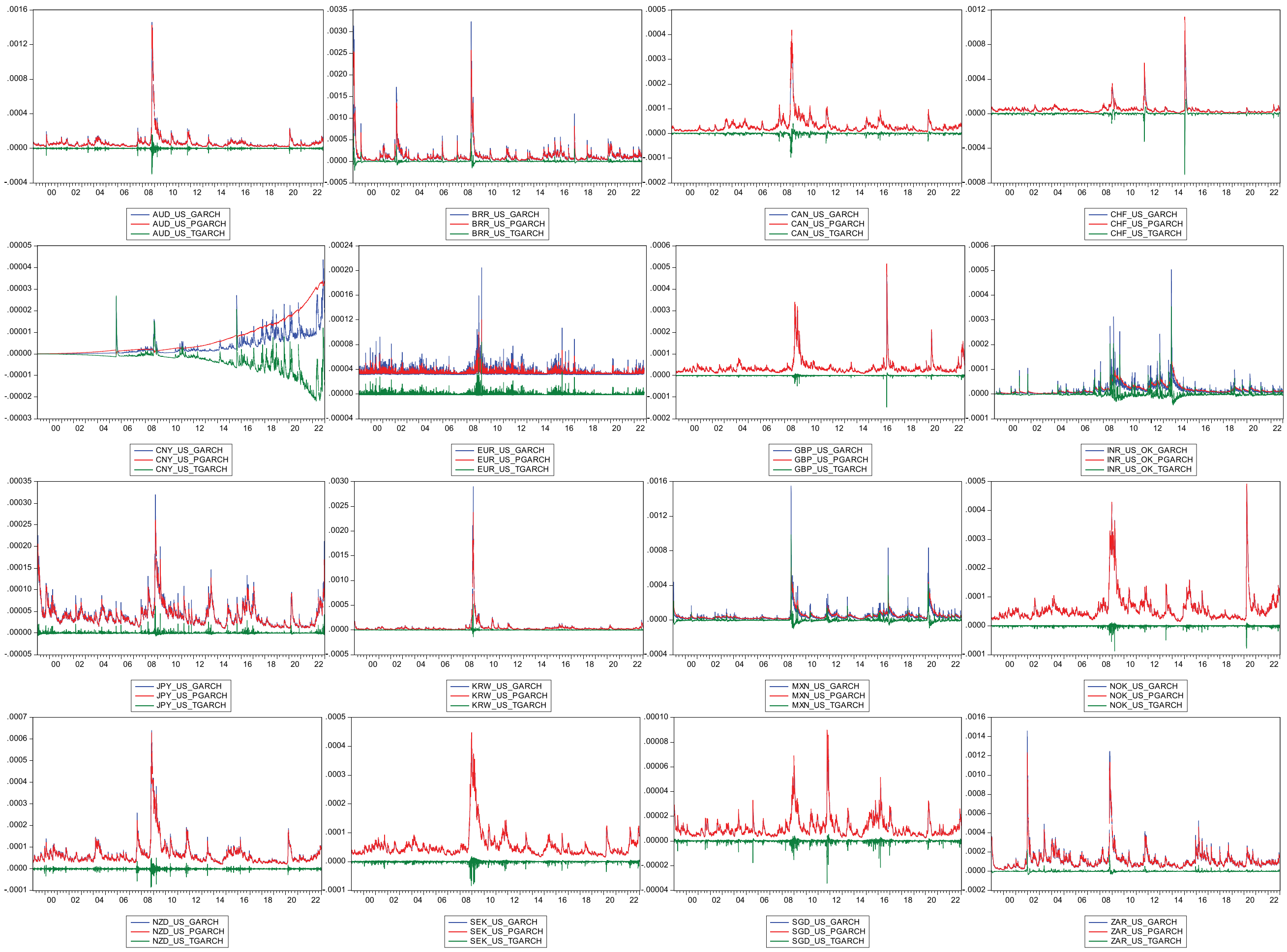

Figure 2. Total, permanent and transitory variance of daily spot exchange rates.

estimated coefficient measuring long-run persistence ($\hat{\rho}$) is large and significant at the 1% level in all cases (except for the EUR). Its magnitude exceeds the coefficients of the transitory component $\left(\hat{\gamma}+\hat{\lambda}\right)$ in all cases, suggesting that the model is stable[3] The coefficient ranges from 0,987 (for GBP) to 0,999 (for CHF and INR), suggesting evidence in favour of a very high volatility persistence; and c) the long-run component ($\hat{\varphi}$), which reflects how shocks affect the permanent component of volatility, imply that the half-life ranges from 55 to 16,503 days showing that permanent conditional volatility presents long memory (column 5 in Table 2).

Regarding the transitory components (columns 6 and 7 in Table 2), we observe that the estimated coefficients are significant in all cases (except for the EUR). In particular: a) the estimated coefficient is significant at 1% level for 12 currencies, at 5% level for three currencies and not significant for the EUR; b) the transitory component persistence $\left(\hat{\gamma}+\hat{\lambda}\right)$ is high for the currencies BEL, CAD, CHF, INR, MXN and ZAR, being the short-run life around five days.

Table 1. The permanent and transitory volatility and events: a summary.

2001 September 11 attacks	Currencies: several. Moderate peaks in volatility.
2008 Global financial crisis	Currencies: all. Strong peaks in volatility. The biggest detected impacts on volatility.
2009 European sovereign debt crisis	Currencies: EUR, GBP, NOK. Moderate peaks in volatility.
2017 Brexit referendum	Currencies: several. Moderate peaks in volatility. Strong peak in volatility: GBP.
2020 COVID-19 pandemic	Currencies: almost all. Moderate and small peaks in volatility.
2022 Ukrainian war	Currencies: almost all. Positive trend in volatility.

[3]In order for the volatility dynamics of Equation (3) to hold, the short-run component of volatility must converge faster than the long-run component..

Table 2. Volatility persistence in daily exchange rates.

Exchange Rate CURRENCY/USD	Permanent component $\hat{\omega}$	$\hat{\rho}$	$\hat{\varphi}$	LR half life[b]	Transitory component $\hat{\gamma}$	$\hat{\lambda}$	SR half life[b]	Wald tests[c] $\hat{\gamma}=\hat{\lambda}=0$	$\hat{\rho}=\hat{\varphi}=0$
AUD	0.000061*	0.991*	0.056*	79	−0.042*	−0.498*	–	97999.4*	34.23*
BRL	0.000227*	0.995*	0.101*	144	0.039*	0.825*	4.74	81092.2*	127.36*
CAD	0.000029*	0.992*	0.056*	93	−0.035*	0.888*	4.36	125030.2*	117.99*
CHF	0.001559*	0.999*	0.055*	4530	−0.041*	0.922*	5.4	1891015*	1950.80*
CNY	0.000006*	0.999*	−0.005*	16503	0.068*	0.909*	31.5	1.19E + 11*	3181394*
EUR	0.000035*	0.500	0.040	1	0.040	0.016	0.24	22.4*	0.80
GBP	0.000036*	0.987*	0.061*	55	−0.022**	0.385	0.68	76460.2*	3.33**
INR	0.000282*	0.999*	0.029*	9627	0.128*	0.758*	5.75	6.75E + 08*	17894.30*
JPY	0.000047*	0.995*	0.040*	144	0.024*	0.353	0.71	351669.4*	5.51*
KRW	0.000073*	0.991*	0.071*	77	0.032*	−0.149	–	136661.3*	3.88**
MXN	0.000056*	0.997*	0.045*	215	0.099*	0.778*	5.34	353183.6*	1222.26*
NOK	0.000062*	0.993*	0.044*	103	−0.022**	−0.054	–	160857.5*	2.62***
NZD	0.000065*	0.992*	0.039*	89	−0.021*	−0.612*	–	145772.2*	16.87*
SEK	0.000051*	0.991*	0.040*	82	−0.029*	0.495***	0.91	121893.3*	8.44*
SGD	0.000010*	0.989*	0.057*	61	−0.040*	0.651*	1.40	120882.9*	28.62*
ZAR	0.000175*	0.996*	0.061*	208	0.015***	0.834*	4.25	176612.5*	19.47*
Residual diagnostics	Q^e_1	Q_4	A_1	A_4	JB				
AUD	0.003 (0.953)	0.539 (0.970)	0.003 (0.952)	0.538 (0.969)	954.98 (0.000)				
BRL	0.040 (0.840)	0.909 (0.923)	0.040 (0.839)	0.906 (0.923)	7233.23 (0.000)				
CAD	0.406 (0.524)	1.940 (0.747)	0.405 (0.524)	1.964 (0.743)	380.83 (0.000)				
CHF	1.347 (0.242)	1.491 (0.828)	1.366 (0.242)	1.484 (0.829)	35681.4(0.000)				
CNY	0.011 (0.913)	0.021 (1.000)	0.011 (0.913)	0.021 (0.999)	215814.56(0.000)				
EUR	1.168 (0.280)	119.730**(0.000)	1.168 (0.279)	115.27**(0.000)	1037.17 (0.000)				
GBP	0.414 (0.520)	19.406**(0.001)	0.414 (0.519)	19.508**(0.000)	952.60 (0.000)				
INR	3.581 (0.058)	4.618 (0.329)	3.579 (0.058)	4.626 (0.327)	24988.89 (0.000)				
JPY	0.034 (0.853)	1.424 (0.840)	0.034 (0.853)	1.429 (0.839)	1927.03 (0.000)				
KRW	0.020 (0.888)	1.929 (0.749)	0.019 (0.887)	1.926 (0.749)	1677.61(0.000)				
MXN	0.409 (0.522)	8.750 (0.068)	0.409 (0.522)	8.873 (0.064)	984.34 (0.000)				
NOK	0.041 (0.839)	9.535** (0.049)	0.041 (0.839)	9.50** (0.049)	816.22 (0.000)				
NZD	0.001 (0.970)	3.324 (0.605)	0.001 (0.969)	3.321 (0.605)	715.14 (0.000)				
SEK	0.130 (0.718)	7.504 (0.112)	0.129 (0.718)	7.486 (0.112)	260.86 (0.000)				
SGD	0.003 (0.952)	0.369 (0.985)	0.003 (0.952)	0.372 (0.984)	1406.70 (0.000)				
ZAR	0.227 (0.634)	2.673 (0.614)	0.227 (0.633)	2.679 (0.612)	356.30 (0.000)				

[a]*, **, *** indicate significance at 1%, 5% and 10%, respectively.
[b]The long-run and short-run half-lives are measured using the following formulae: $LR_{HL}(\hat{\rho}) = Ln(1/2)/Ln(\hat{\rho})$ and $SR_{HL}(\hat{\gamma}+\hat{\lambda}) = Ln(1/2)/Ln(\hat{\gamma}+\hat{\lambda})$.
[c]Wald tests on coefficient restrictions are Chi-square statistics with 2 degrees of freedom.
[d]USD: United States Dollar, Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), European euro (EUR), Great Britain pound sterling (GBP), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krone (SEK), Singapore dollar (SGD) and South African rand (ZAR).
[e]Qi denotes an ith order Ljung-Box test, Ai denotes an ith order ARCH LM test and JB denotes the Jarque-Bera test for residual normality.

It is worth noting that for the currency CNY, the transitory persistence is much higher (0.977), implying that the short-run component half-life decay in 31.5 days. Nevertheless, the estimated long-term half-lives are greater than the corresponding short-term half-lives (column 8 in Table 2). This indicates that the exchange rate adjusts over longer periods to align with economic fundamentals, while temporary shocks are absorbed more rapidly, in line with S. S. Chen and Chou (2015).

All these P-T empirical results are consistent with the scarce previous existing evidence, such as, for example, the case of the contribution Ndou, Gumata, and Ncube (2017). These authors decompose the overall volatility for the rand per US dollar (from January 1990 to December 2014) into P-T volatility components and obtain that the long-run component volatility is highly persistent, displaying more persistent than transitory volatility.

The results for the EUR are also consistent with those of the previous literature. The volatility of the euro exchange rate can vary significantly due to the complex interplay of internal and external factors affecting the euro area. These factors include divergent monetary policies, the diverse economic conditions of the eurozone countries, market expectations regarding measures from the European Central Bank or the fiscal policies of individual eurozone countries, speculation in financial markets, and political or economic events that can impact both the euro area and the global economy, such as the European sovereign debt crisis or Brexit, given that EUR constitutes an important international currency, which has implications for other countries as well as for monetary policy in the euro area (Buti and Corsetti 2024; Germain and Schwartz 2014). Its differentiated behaviour could be explained, for instance, by the findings of McMillan and Speight (2010), who, analysing the volatility spillovers of the euro exchange rates to the US dollar, Japanese yen, and British pound sterling, found that the dollar rate dominates the other two rates.

The analysis presented in columns 9 and 10 of Table 2 strongly illustrates that the C-GARCH model proves effective for all currencies, with the notable exception of the EUR. This highlights the model's robustness in capturing market dynamics across most currencies.

Finally, columns 12 to 15 in Table 2 show the residual diagnostics of these models. The results confirm the presence of residual non-normality. Additionally, the Ljung Box and ARCH LM statistics generally indicate evidence in favour of no autocorrelation.

Step 2: correlation analysis and principal components analysis

To gain further insights in the behaviour of the permanent and transitory components of the conditional variance, we examine the correlation coefficients between each series. Tables 3 and 4 show the correlation coefficients between the permanent and transitory components, respectively. In general, results suggest that there is a stronger correlation between the permanent components than between the transitory components series. In particular, for

Table 3. Correlation coefficients: permanent volatility components.

	AUD	BRL	CAD	CHF	CNY	EUR	GBP	INR	JPY	KRW	MXN	NOK	NZD	SEK	SGD	ZAR
AUD	1.000	0.609	0.843	0.225	−0.115	0.416	0.637	0.366	0.622	0.931	0.728	0.668	0.888	0.657	0.545	0.687
BRL		1.000	0.485	0.133	−0.054	0.238	0.332	0.080	0.577	0.595	0.582	0.341	0.473	0.305	0.383	0.494
CAD			1.000	0.303	−0.125	0.444	0.682	0.413	0.594	0.771	0.685	0.739	0.864	0.777	0.640	0.684
CHF				1.000	−0.163	0.282	0.208	0.116	0.248	0.170	0.156	0.310	0.320	0.344	0.369	0.182
CNY					1.000	−0.159	0.002	−0.091	−0.262	−0.081	0.141	0.016	−0.195	−0.144	−0.113	−0.106
EUR						1.000	0.394	0.163	0.354	0.344	0.300	0.446	0.474	0.505	0.394	0.329
GBP							1.000	0.308	0.580	0.590	0.616	0.728	0.716	0.694	0.485	0.531
INR								1.000	0.241	0.323	0.361	0.437	0.459	0.499	0.323	0.197
JPY									1.000	0.589	0.530	0.540	0.666	0.559	0.481	0.456
KRW										1.000	0.666	0.550	0.777	0.541	0.470	0.666
MXN											1.000	0.739	0.693	0.597	0.578	0.587
NOK												1.000	0.805	0.846	0.627	0.499
NZD													1.000	0.844	0.650	0.625
SEK														1.000	0.619	0.510
SGD															1.000	0.511
ZAR																1.000

Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), European euro (EUR), Great Britain pound sterling (GBP), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK), Singapore dollar (SGD) and South African rand (ZAR).

Table 4. Correlation coefficients: transitory volatility components.

	AUD	BRL	CAD	CHF	CNY	EUR	GBP	INR	JPY	KRW	MXN	NOK	NZD	SEK	SGD	ZAR
AUD	1.000	−0.153	0.138	0.018	−0.025	−0.247	0.156	−0.017	−0.307	−0.054	−0.221	0.319	0.791	0.170	0.120	−0.096
BRL		1.000	−0.294	−0.018	0.045	0.054	−0.082	0.015	0.122	0.155	0.517	−0.098	−0.082	−0.113	−0.123	0.295
CAD			1.000	0.052	−0.091	−0.207	0.181	−0.095	−0.123	−0.163	−0.464	0.225	0.117	0.375	0.313	−0.405
CHF				1.000	−0.021	−0.121	0.036	−0.015	−0.050	−0.005	−0.018	0.057	0.028	0.076	0.092	−0.004
CNY					1.000	0.108	−0.025	0.054	0.035	0.025	0.089	−0.028	−0.019	−0.041	−0.060	0.042
EUR						1.000	−0.318	0.055	0.264	0.019	0.088	−0.596	−0.320	−0.589	−0.289	0.102
GBP							1.000	−0.036	−0.316	−0.085	−0.136	0.325	0.184	0.320	0.171	−0.150
INR								1.000	0.027	−0.015	0.082	−0.057	−0.022	−0.053	−0.108	0.049
JPY									1.000	0.059	0.170	−0.255	−0.278	−0.244	−0.207	0.136
KRW										1.000	0.214	−0.070	−0.028	−0.080	−0.153	0.176
MXN											1.000	−0.162	−0.119	−0.152	−0.225	0.404
NOK												1.000	0.387	0.561	0.293	−0.134
NZD													1.000	0.201	0.135	−0.087
SEK														1.000	0.354	−0.198
SGD															1.000	−0.233
ZAR																1.000

Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), European euro (EUR), Great Britain pound sterling (GBP), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK), Singapore dollar (SGD) and South African rand (ZAR).

permanent components, correlations over 0,70 or more are detected in 15 out of 120 possible cases between the pair of currencies AUD-CAD, AUD-KRW, AUD-MXN, AUD-NZD, CAN-KRW, CAN-NOK, CAN-NZD, CAN-SEK, GBP-NOK, GBP-NZD, KRW-NZD, MXN-NOK, NOK-NZD, NOK-SEK and NZD-SEK. Moreover, correlation between 0.70 and 0.50 is detected in 43 out of 120 possible cases. In this regard, it should be noted that through their analysis of high-frequency hourly data, Kang and Cabaero (2025) reveal a compelling link between third-party foreign exchange trading volumes and the volatilities of original currency pairs. This finding underscores the critical role that external trading dynamics play in shaping currency market behaviour and highlights the importance of considering these factors for a deeper understanding of foreign exchange fluctuations. The USD, the leading currency, has a significant influence through this third-party channel, and the extent of foreign exchange trading volume proves to be a key factor in this impact.

For transitory components, strong correlation (0.791) is detected only for the pair of currencies AUD-NZD, reflecting that Australia and New Zealand have one of the world's closest, broadest, and most mutually compatible economies, sharing several structural characteristics and having close ties in trade, financial, and geographical terms.

We proceed to analyse the similarity of volatility trends among the examined currencies. As indicated in Table 5, the principal component analysis of the permanent volatility components reveals a significant degree of co-movement for most of the currencies studied. Notably, the weights of the first principal component are similar in both sign and absolute value for all currencies, with the exception of BRL, CHF, CNY, EUR, and INR. These results can be interpreted as evidence of a common underlying trend among the other currencies. Moreover, the principal component analyses for the transitory volatility component indicate that these components share less similarity than the permanent components (Table 6). The transitory component's weights exhibit significantly more dispersion and total variability than the permanent component. Given that the transitory volatility component represents transient and *ad hoc* disruptions, this is unsurprising and is consistent with earlier findings reported by Black and McMillan (2004) and Pramor and Tamirisa (2006).

Step 3: cluster analysis

This subsection examines whether cluster analysis can identify comparable characteristics among the investigated currencies. This approach is used to analyse both the permanent and transitory elements of exchange rate volatility.

Looking at the results of the hierarchical method,[4] choosing two or three clusters for the permanent component and three for the temporary component is the best option. The *k*-means algo-

[4]These additional results are not shown here to save space, but they are available from the authors upon request.

Table 5. Principal components of long-run volatility.

	C1[a]	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
Eigenvalues	8.493	1.3615	1.2106	0.9290	0.7343	0.6153	0.5794	0.5314	0.3602	0.3201	0.2585	0.2303	0.1493	0.1058	0.0883	0.0323
Variance Proportion	53,08%	8,51%	7,57%	5,81%	4,59%	3,85%	3,62%	3,32%	2,25%	2,00%	1,62%	1,44%	0,93%	0,66%	0,55%	0,20%
Cumulative Proportion	53,08%	61,59%	69,16%	74,96%	79,55%	83,40%	87,0%	90,34%	92,6%	94,60%	96,21%	97,65%	98,50%	99,25%	99,8%	100,0%
Eigenvectors																
AUD[b]	0.3104	0.1759	−0.1046	−0.1062	0.0008	0,2134	0,0096	0,2316	−0,2810	0,0605	−0,0738	−0,0491	0,1622	−0,0022	0,2380	−0,7601
BRL	0.2052	0.3815	−0.3683	0.1265	0.2088	−0,2558	0,4056	−0,0314	0,0926	−0,2981	0,1217	0,5100	0,0751	0,0709	0,0241	0,0498
CAD	0.3121	0.0011	0.0142	−0.0493	−0.0049	0,1940	−0,1135	0,0233	−0,1563	0,0368	0,2491	0,1672	−0,8298	0,2068	−0,0008	0,0406
CHF	0.1212	−0.4611	−0.1259	0.5251	0.5374	0,1257	−0,0658	0,3812	0,1242	−0,0507	−0,0827	−0,0344	−0,0059	−0,0235	−0,0003	−0,0030
CNY	−0.0471	0.4438	0.6094	0.4418	0.0421	0,0227	0,1455	0,1846	0,0534	0,2854	0,2921	−0,0106	0,0383	−0,0302	0,0664	0,0067
EUR	0.1825	−0.2923	−0.0862	0.2898	−0.6409	0,1440	0,5717	0,0653	0,0919	0,0451	−0,0915	−0,0722	−0,0427	0,0110	0,0212	0,0257
GBP	0.2675	0.0067	0.1796	0.0444	−0.2621	−0,2424	−0,4084	0,1500	0,3451	0,1545	−0,4537	0,4716	−0,0075	−0,0497	0,0432	−0,0376
INR	0.1589	−0.2239	0.3681	−0.5739	0.3183	0,0578	0,4467	0,1016	0,3485	0,1092	−0,0420	0,0603	0,0086	0,0685	0,0392	−0,0103
JPY	0.2506	0.0099	−0.2825	−0.0457	0.0024	−0,6177	−0,0284	0,1014	0,2000	0,3985	0,2561	−0,4352	−0,0720	0,0273	−0,0122	−0,0512
KRW	0.2843	0.2583	−0.1461	−0.1310	0.0202	0,2652	0,0034	0,3091	−0,2171	0,2581	−0,1802	−0,0536	0,2025	0,0548	−0,5624	0,3718
MXN	0.2765	0.2656	0.1783	0.0771	0.1317	−0,1180	0,1162	−0,1542	−0,0069	−0,3710	−0,4676	−0,4333	−0,2745	−0,3535	−0,0181	0,0438
NOK	0.2899	−0.1097	0.3015	0.0787	−0.0596	−0,1904	−0,1113	−0,0727	−0,1305	−0,3710	0,0309	−0,1556	0,2421	0,7097	−0,0833	0,0128
NZD	0.3226	−0.0696	0.0129	−0.1066	−0.0292	0,0286	−0,0966	0,0898	−0,2671	−0,0081	0,1322	−0,0041	0,2129	−0,2014	0,6593	0,5009
SEK	0.2899	−0.2528	0.2007	−0.0429	−0.1066	−0,0948	−0,0954	−0,0326	−0,0831	−0,2494	0,4575	0,1432	0,1403	−0,5190	−0,4142	−0,1406
SGD	0.2486	−0.1548	0.0380	0.1948	0.2229	0,0152	0,0814	−0,7096	−0,2202	0,4637	−0,1346	0,1379	0,1005	−0,0008	−0,0421	−0,0467
ZAR	0.2503	0.1894	−0.1576	0.0356	−0.0336	0,4901	−0,2283	−0,2841	0,6244	−0,0794	0,2168	−0,1825	0,1439	0,0344	0,0517	0,0113

[a] C_i denotes an *i*th Principal component with $i = 1, \ldots 16$.
[b] Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), European euro (EUR), Great Britain pound sterling (GBP), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK), Singapore dollar (SGD) and South African rand (ZAR).

Table 6. Principal components of short-run volatility.

	C1[a]	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
Eigenvalues	3.8111	1.8744	1.4421	1.0531	0.9880	0.9588	0.9170	0.9009	0.7703	0.7136	0.6111	0.5775	0.4515	0.3805	0.3565	0.1928
Variance Proportion	23,82%	11,72%	9,01%	6,58%	6,18%	5,99%	5,73%	5,63%	4,81%	4,46%	3,82%	3,61%	2,82%	2,38%	2,23%	1,21%
Cumulative Proportion	23,82%	35,54%	44,55%	51,13%	57,31%	63,30%	69,0%	74,66%	79,5%	83,94%	87,76%	91,37%	94,19%	96,57%	98,8%	100,0%
Eigenvectors																
AUD[b]	0,2823	0,2316	−0,5594	−0,1024	0,0402	0,0390	0,0640	0,1092	0,0546	0,0753	0,0903	0,0344	0,0685	−0,0622	0,1606	0,6869
BRL	−0,1988	0,3971	0,2130	−0,0373	−0,0793	0,0093	−0,1122	0,2792	0,3956	0,4217	−0,0516	0,2425	−0,4761	−0,1195	0,1495	0,0046
CAD	0,2933	−0,3265	0,1015	−0,0525	−0,0334	0,0597	0,2114	−0,0189	0,1630	0,2748	0,1923	0,6515	0,1427	0,1084	−0,3847	0,0308
CHF	0,0622	0,0401	0,1526	−0,2041	0,9058	0,2453	−0,0974	−0,0777	−0,0769	0,1460	−0,0231	−0,0135	−0,0188	0,0600	0,0385	0,0014
CNY	−0,0644	0,0627	−0,0671	0,5921	−0,0470	0,7821	0,0586	0,0013	−0,0439	−0,0436	−0,0052	0,0486	−0,0281	−0,0991	−0,0515	0,0040
EUR	−0,3355	−0,2756	−0,2710	0,0180	−0,0086	0,0926	−0,1747	0,0120	0,1782	0,0712	0,1967	0,0895	0,0284	0,6742	0,3942	−0,0638
GBP	0,2539	0,1071	0,1442	0,2244	−0,1174	−0,0893	−0,4956	−0,2979	−0,1911	0,3891	0,5243	−0,1770	0,0403	−0,0210	0,0184	0,0181
INR	−0,0641	0,0522	−0,1078	0,6499	0,3522	−0,5027	0,2987	−0,1238	0,2522	−0,0263	0,0984	0,0144	−0,0598	−0,0044	−0,0108	−0,0050
JPY	−0,2552	−0,1243	0,1101	−0,0966	−0,0125	0,0475	0,5797	0,2961	−0,2765	0,3407	0,4172	−0,3046	0,0131	−0,0754	0,0713	0,0393
KRW	−0,1200	0,2493	0,0323	−0,2725	−0,1145	0,1707	0,3477	−0,7566	0,2907	−0,0374	0,1290	−0,0761	−0,0516	0,0268	0,0281	0,0046
MXN	−0,2651	0,4379	0,1835	0,0454	−0,0138	−0,0169	−0,0498	0,1412	0,1310	0,1196	−0,1103	−0,0918	0,6704	0,2646	−0,3036	0,1251
NOK	0,3556	0,2455	0,1571	0,0698	−0,0755	−0,0035	0,2008	0,0639	−0,2300	−0,0641	−0,1104	−0,1469	−0,4133	0,6517	−0,2025	0,0799
NZD	0,2855	0,3086	−0,4891	−0,0993	0,0259	0,0456	0,0997	0,1451	0,0615	0,1461	0,0792	−0,0521	0,1118	−0,0034	−0,0411	−0,7015
SEK	0,3486	0,1214	0,3601	0,1016	−0,0677	−0,0055	0,2155	0,0082	−0,0725	−0,0307	−0,1261	0,2006	0,3196	0,0184	0,7088	−0,0732
SGD	0,2696	−0,0829	0,2391	−0,0603	0,0395	0,1283	−0,0517	0,2969	0,5678	−0,4143	0,4104	−0,2949	0,0177	−0,0102	−0,0238	0,0149
ZAR	−0,2313	0,3740	0,0147	−0,0757	0,0663	−0,0589	−0,0401	0,0779	−0,3343	−0,4804	0,4720	0,4637	−0,0549	−0,0123	−0,0109	−0,0386

[a] C_i denotes an *i*th Principal component with $i = 1, \ldots 16$.
[b] Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), European euro (EUR), Great Britain pound sterling (GBP), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK), Singapore dollar (SGD) and South African rand (ZAR).

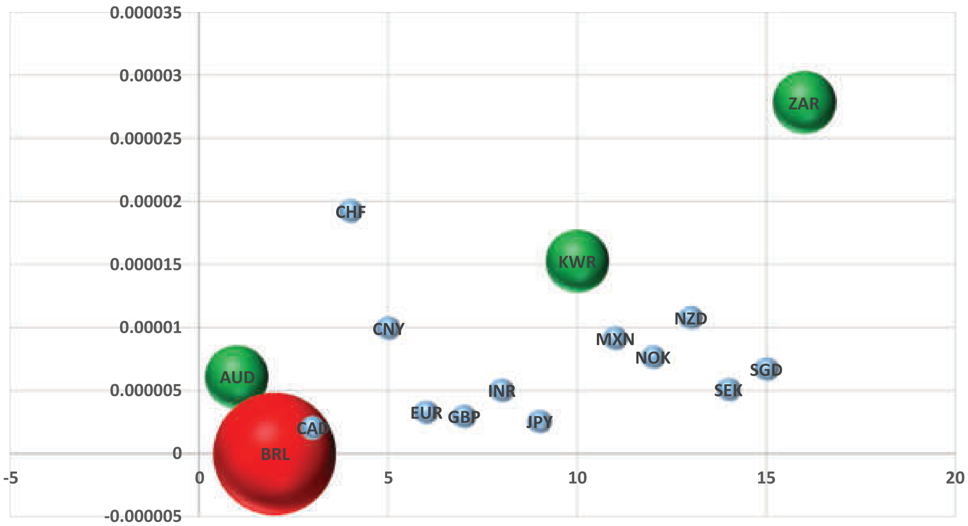

Figure 3. Centroids and distance inter clusters: permanent components.
The size of the balls represents the value of the centroid (i.e. the average behaviour of the cluster with respect to the permanent volatility). The vertical axis represents the inter cluster distance and the horizontal axis represents the number of countries.

rithm chooses three groups. As a result, we should choose 3 clusters for both the temporary component and the permanent one.

Regarding permanent volatility, the results for $m = 3$ groups determine that CAD, CHF, CNY, EUR, GBP, INR, JPY, MXN, NOK, NZD, SEK and SGD are included in the first cluster, BRL in the second and AUD, KWR and ZAR in the third cluster. Figure 3 illustrates these results. The vertical axis represents the inter-cluster distance, and the horizontal axis represents the number of currencies. The balls' size represents the cluster centre's value, which can be interpreted as the average behaviour of the cluster concerning the permanent volatility (i.e. the bigger the ball, the higher the permanent volatility). The currencies in the first cluster share the characteristic of being classified as 'major currencies' or 'emerging market currencies' in international currency markets. They are typically traded with high frequency, which provides them with significant liquidity. Most of these currencies operate under a floating exchange rate regime, with the exceptions being CNY, INR, and SGD, which are managed floating rates (Ilzetzki, Reinhart, and Rogoff 2019). Additionally, many of these currencies belong to countries with large economies or regional significance, which affects their stability and presence in global markets. For its part, the currency in the second cluster (BRL) is characterized by a soft peg-wide exchange rate regime, while the currencies in the third cluster either follow a freely floating exchange rate regime (AUD) or have a soft peg-wide exchange rate regime (KWR and ZAR) (Ilzetzki, Reinhart, and Rogoff 2019).

As for the transitory volatility, the algorithm clearly identifies three clusters: Group 2 formed by MXM; Group 3 composed of BRL; and Group 1 consisting of the rest of the currencies under study. The fact that MXN may constitute a special case of a transitory volatility component could be explained by several factors. These include its reliance on oil prices since Mexico is a major oil producer and exporter. Additionally, as an 'emerging market' currency, it is more susceptible to fluctuations in international financial markets. Investment flows also influence MXN, as Mexico attracts foreign direct investment and speculative capital. Finally, its relationship with the monetary policy of the U.S. Federal Reserve plays a significant role in its volatility. Figure 4 illustrate these results. Regarding BRL, its relevance arises from the interaction of factors such as political instability (Brazil has experienced significant political and social fluctuations), dependence on commodity exports (Brazil is a major exporter of products such as soybeans, iron, oil and other natural resources), changes in investment flows (very sensitive to both internal and global factors), and interventions by the Central Bank of Brazil. As can be seen, the size of the ball in Group 2 is bigger than that for Group 3, and both much

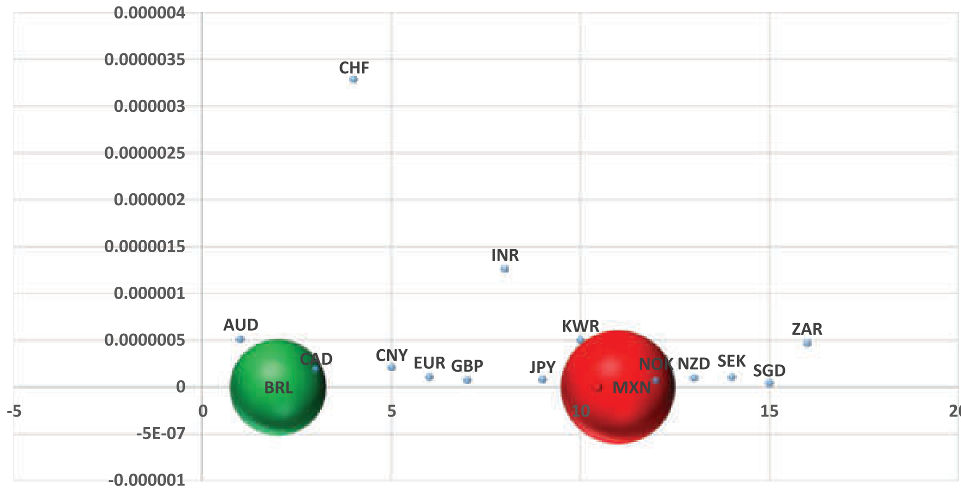

Figure 4. Centroids and distance inter clusters: transitory components.
The size of the balls represents the value of the centroid (i.e. the average behaviour of the cluster with respect to the transitory volatility). The vertical axis represents the inter cluster distance and the horizontal axis represents the number of countries.

bigger that balls in Group 1. It is also worth noting that within Group 1, CHF is very distant from the rest, possibly reflecting its role as a 'safe-haven currency' (Grisse and Nitschka 2015).

Step 4: drivers of transitory volatility components[5]

With the empirical analysis of step 4, we try to answer our last relevant question: Is the detected transitory volatility component related to market sentiment and financial tensions? To that end and to gain further insights, given that previous research indicates that expectations about the fundamentals are more significant over longer horizons compared to shorter horizons (see, e.g. Beckmann and Czudaj 2024; Kouwenberg et al. 2017), we empirically investigate the relationship between the detected transitory volatility components and measures of market sentiment and financial tensions using four leading daily uncertainty indicators[6] the Equity Market-related Economic Uncertainty Index (EMEU),[7] the stock market volatility (VIX) index,[8] the Economic Policy Uncertainty (EPU) index,[9] and the Geopolitical risk (GPR) index.[10] Results in Table 7 suggest that economic policy uncertainty and geopolitical risk intensify transitory volatility[11], aligning with the flight-to-quality phenomenon (e.g. Csontó 2014) and the findings of Bartsch (2019), who points out that, whether small or large, events can significantly increase market uncertainty related to policy decisions. Furthermore, Pástor and Veronesi (2013) highlight the vital role of political uncertainty in

[5]We focus on analysing the key factors affecting the transitory components of volatility. The permanent components are linked to long-term structural changes in the market caused by shocks to economic fundamentals. To accurately identify the determinants of these permanent volatility components, it would be crucial to have daily data on these variables. However, the absence of such data at a daily frequency limits our analytical capacity, further highlighting the importance of developing new sources of information to improve understanding of these phenomena.

[6]We thank an anonymous referee for recommending the inclusion of macroeconomic and financial variables as possible explanatory variables. Their selection depended on their daily availability. The change in the U.S. Federal Funds Effective Rate (reflecting monetary policy measures), the TED spread (which is the difference between the three-month Treasury bill and the three-month LIBOR based on U.S. dollar, proxying global funding liquidity risk), and the MOVE bond market volatility index (capturing Treasury rate volatility through options pricing) were also initially considered as potential explanatory variables in a general statistical model. However, these variables were statistically insignificant in the regression results and were eliminated according to the general-specific approach (Hendry 1995, ch. 9).:

[7]EMU is constructed by analysing newspaper articles containing terms related to equity market uncertainty (see Baker, Bloom, and Davis 2022a). Source: https://www.policyuncertainty.com/.

[8]VIX is constructed by the Chicago Board Options Exchange and reflects a volatility index measuring market expectation of near-term volatility conveyed by stock index option prices. It was considered the 'fear gauge' of financial markets by market participants and media (Whaley 2000). This series is downloaded from Refinitiv Datastream.

[9]EPU is based on daily news from newspapers and measures the uncertainty in monetary, fiscal, and other relevant policies (Baker, Bloom, and Davis 2022b). Source: https://www.policyuncertainty.com/.

[10]GPR is a measure of adverse geopolitical events and associated risks based on a tally of newspaper articles covering geopolitical tensions constructed by. Caldara and Iacoviello (2022). Source: https://www.matteoiacoviello.com/gpr.htm.

[11]Given that the explanatory variables are generated regressors that could bias estimates (Pagan 1984), the t-statistics in Table 6 are based on robust standard errors computed using the pairs cluster (or non-overlapping block) bootstrap method (Cameron, Gelbach, and Miller 2008). W. Chen, Hribar, and Melessa (2023) demonstrate that this method effectively eliminates the generated regressor bias and offers several significant benefits in most empirical research.

Table 7. Drivers of transitory volatility components: estimated regressions.

	AUD	BRL	CAD	CHF	CNY	EUR	GBP	INR	JPY	KRW	MXN	NOK	NZD	SEK	SGD	ZAR
EMEU	3.32E−9*	3.18E−9*	2.16E−9	1.18E−9	4.83E−9*	1.10E−9*	1.40E−9*	4.71E−9*	2.08E−9*	5.06E−9*	5.28E−9*	1.09E−9*	1.91E−9*	8.77E−9*	2.76E−9**	4.67E−9*
	(4.0027)	(5.0237)	(3.0060)	(3.7830)	(5.4023)	(3.2520)	(3.2535)	(3.0403)	(5.4189)	(3.5782)	(4.3736)	(3.3139)	(3.7678)	(3.1722)	(2.3589	(3.4671)
EPU	1.51E−9*	1.24E−9*	6.32E−9	2.63E−9	1.58E−9*	1.96E−9*	7.60E−9*	9.29E−9*	1.07E−9**	8.35E−9*	2.43E−9*	2.53E−9*	8.92E−9*	2.16E−9*	5.81E−9*	1.88E−9*
	(3.9155)	(3.7191)	(4.3901)	(4.0148)	(4.1726)	(4.0898)	(3.0175)	-3.6753]	(2.5349)	(3.2762)	(3.9172)	(4.2865)	(3.6671)	(3.2956)	(3.6013)	(3.2692)
VIX	1.54E−9*	1.26E−9*	9.98E−9	5.59E−9	4.469E**	4.36E−9*	1.56E−9*	4.76E−9**	9.94E−9*	1.65E−9*	4.33E−9*	2.63E−9*	1.42E−9*	4.59E−9*	9.45E−9*	1.80E−9*
	(3.0476)	(4.0026)	(4.6329)	(4.0388)	(2.3483)	(5.5415)	(4.1829)	(2.3940]	(2.9933)	(3.3489)	(3.8125)	(3.5651)	(3.7181)	(3.5412)	(4.1126)	(3.5161
GPR	3.06E−9*	3.91E−9*	1.06E−9	0.68E−9	1.03E−9*	4.75E−9*	2.52E−9*	3.45E−9**	2.11E−9*	2.91E−9*	7.70E−9*	2.45E−9*	1.08E−9*	5.22E−9*	1.15E−9*	5.32E−9*
	(4.0146)	(5.3014)	(4.0136)	(3.9920)	(4.8726)	(6.6172)	(5.2080]	(2.3361)	(4.8798)	(3.8343)	(5.0122)	(3.6223)	(3.4937)	(3.9871)	(4.0104)	(3.5114)
Adjusted R^2	0.7547	0.8096	0.8147	0.7964	0.7991	0.8326	0.8061	0.8165	0.8235	0.8184	0.7733	0.7981	0.7798	0.7631	0.8065	0.8113

EMEU, EPU, VIX and GPR denote the Equity Market-related Economic Uncertainty Index, the stock market volatility index, the Economic Policy Uncertainty index and the Geopolitical Risk index, respectively.
Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), Swiss franc (CHF), Chinese yuan renminbi (CNY), European euro (EUR), Great Britain pound sterling (GBP), Indian rupee (INR), Japanese yen (JPY), South Korean won (KRW), Mexican peso (MXN), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK), Singapore dollar (SGD) and South African rand (ZAR).
In parenthesis below the parameter estimates are the corresponding *t*-statistics, based on robust standard errors computed using the pairs cluster bootstrap method (Cameron, Gelbach, and Miller 2008). * and ** denote significance at the 1% and 5% level, respectively.

markets as investors struggle to predict how policymakers will respond. Moreover, in line with Engle and Lee (1999) and Pramor and Tamirisa (2006), who argue that investor confidence affects the transitory component of volatility, the estimated coefficients for EMEU and VIX are also positive and significant, suggesting that transitory volatility is exacerbated by financial stress. One reason for this result may be that market uncertainty and volatility affect noise traders who enter the market and increase the transitory volatility in the process. Note that our finding is consistent with Campbell, Grossman, and Wang (1993), who argue that changes in investor sentiment can trigger strong liquidity shocks with a significant impact on volatility, and Baek, Bandopadhyaya, and Du (2005), who contend that changes in investor sentiment explain asset price movement in the short-term better than fundamental factors. One explanation for this reason could be that a positive change in investor sentiment affects noise traders who enter the market and increases the transitory volatility in the process.

IV. Concluding remarks and policy implications

The interdependence of financial markets has a significant impact on the financial decisions of many market players, making it crucial to detect risk spillovers. Given the substantial impact that exchange rate volatility has on global trade and financial markets, it is essential to understand the intricate interactions between the volatilities of major currencies.

The latest empirical evidence on the dynamics of volatility in daily exchange rates indicates that volatility consists of several components. Since fluctuations in exchange rate returns play a crucial role in portfolio management, obtaining accurate estimates of volatility is essential. In this context, our contribution to the existing literature involves an empirical evaluation of the transitory and permanent components of exchange rate volatility. We achieve this by applying the component-GARCH model, as proposed by Engle and Lee (1999), to daily spot data for sixteen major currencies relative to the US dollar, spanning the period from 1999 to 2023. This model provides significant flexibility for modelling and analysing financial time series that exhibit complex volatility behaviours, being this flexibility crucial in a financial environment commonly characterized by high volatility events and unexpected structural changes.

The main results of this analysis can be summarized as follows. The results obtained in step 1 suggest that the temporal evolution of the permanent and transitory volatility components capture the most relevant events of the 21st century, showing that the persistence of volatility with long memory is much greater in the permanent component of volatility than in the transitory. This evidence reveals that, in policy terms, the P-T decomposition of volatility is useful because, first, it is relevant for policymakers to distinguish the sources of volatility shocks, and second, permanent volatility would drive policy responses while transitory volatility would not.

From step 2, correlation analysis and principal components analysis, we observe that the cross-country correlations between currencies are lower for the transitory component than the permanent component. Moreover, the principal component analysis of the permanent volatility components suggests evidence of a common underlying trend among currencies. However, the results for the transitory volatility component indicate that these components share less similarity than the permanent components.

The cluster analysis results of step 3 detect the existence of three groups of currencies in our sample, both in permanent and transitory components of volatility, classifying the majority of the currencies in one of them.

From step 4, we find that the transitory component is closely associated with measures of market sentiment and financial tensions, further supporting the presence of animal spirits driving financial decision-making in uncertain environments and volatile times (Keynes 1937).

All in all, our empirical findings reveal that foreign exchange markets adequately capture financial and macroeconomic shocks (Gabaix and Maggiori 2015), incorporating trends in the evolution of fundamental economic variables, geopolitical developments and market sentiment and acting as a barometer for financial market turmoil (Chernov, Haddad, and Itskhoki 2024).

Although it is imperative to recognize that the foreign exchange market is subject to a complex interaction between several factors, our results suggest that shocks to economic fundamentals (captured in the permanent volatility component) and market sentiment (captured by transient volatility) feed each other, transmitting and intensifying tensions at a global level and creating a intricate and densely interconnected network.

Analysts and risk managers benefit from breaking down volatility into permanent and temporary components. By gaining a clearer understanding of the sources of volatility, they can make informed decisions about mitigating risks associated with market price fluctuations. Furthermore, by identifying temporary components, analysts can differentiate between changes that may quickly reverse and those that are likely to be more enduring.

Further research is needed to explore the potential effects of macroeconomic events in various countries on the temporary component of exchange rate volatility. Additionally, our findings underscore the need for a comprehensive analysis of the euro's differentiated behaviour. Finally, we could also utilize the alternative permanent-transitory decomposition approach introduced by Gonzalo and Ng (2001) to analyse the contributions of permanent and transitory shocks in explaining exchange rates and economic fundamentals. These topics will be part of our future research agenda.

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