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Xu, Lei
Kinkyo, Takuji

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Lei Xu
Takuji Kinkyo

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Classifying Currencies Using Common Factors

Lei Xu[a]
Takuji Kinkyo[b]

This study proposes a novel approach for classifying currencies on the basis of common driving forces that determine their behavioral features. In contrast with the conventional approach, which focuses on exchange rate systems that regulate variations in currencies, and classifies them according to the anchor currency and system flexibility of the system, we focus on the common factors that govern the dynamic behavior of currencies. We employed a multivariate factor stochastic volatility model to estimate the latent factors and applied *K*-means and hierarchical clustering to the estimated factor loadings. We observed three distinct clusters that can be labeled the US dollar, euro, and commodity currency blocks. This approach will prove particularly useful for investors and policymakers to evaluate the currency risks that are common within a currency block, but vary between different blocks.

Keywords stochastic volatility model, cluster analysis, foreign exchange rate, currency classification, global financial cycle

1 Introduction

In this study, we propose a novel approach to classify currencies. The conventional approach focuses on exchange rate systems that regulate variations in currencies, and classifies them according to the anchor currency and the flexibility of the system, for example, by the intensity of official intervention in foreign exchange markets (Levy-Yeyati and Sturzenegger, 2003; Reinhart and Rogoff, 2004, Shambaugh, 2004; Ilzetzki et al., 2019). However, we focus on the common factors that govern the dynamic behavior of currencies. We choose this approach because recent studies on financial globalization find a high degree of co-movement in asset prices, com-

a Department of Law, Economics and Management, Okinawa University, Graduate School of Economics, Kobe University, r-jyo@okinawa-u.ac.jp
b Graduate School of Economics, Kobe University, kinkyo@econ.kobe-u.ac.jp

modity prices, and capital flows across the globe, a phenomenon called the Global Financial Cycle (GFC), which is driven by a small number of common global factors (Miranda-Agrippino and Rey, 2022). We use the multivariate factor stochastic volatility (SV) model developed by Kastner et al. (2017) and Kastner (2019) to identify the common latent factors that determine the behavioral features of currencies. We then classify them by applying clustering analyses to the estimated factor loadings.

This method demonstrates two key advantages. First, it classifies currencies according to similarities in exchange rate behavior, rather than the flexibility of exchange rate systems. Therefore, it helps identify "currency blocks," that is, currencies driven by common factors, and provides guidance for exchange rate forecasting, primarily because the currencies in the same block are likely to react in a similar manner to shocks affecting the underlying driving forces. Second, the method is based on statistical data analysis and involves only few elements of subjective judgement. This is essential for identifying *de facto* exchange rate systems that differ from the *de jure* ones. By applying this method to the daily prices of gold and the exchange rates of 30 major currencies, we identify the US dollar (USD), Euro (EUR), and commodity currency blocks.

The remainder of this paper is organized as follows. A brief survey of related studies is presented in Section 2. The methods and data are described in Section 3. Section 4 presents the empirical results. Finally, the conclusions are provided in Section 5.

2 Related Works

2.1 Global Financial Cycles

The recent studies show that the GFC is crucial for understanding the economic dynamics that affect asset prices, global capital flows, commodity prices, international trade, and world output (Miranda-Agrippino and Rey, 2022). Structural shocks influencing global financial conditions, a key driver of the GFC, have varying impacts on the economic dynamics; particularly significant among these are U.S. monetary policy shocks (Miranda-Agrippino and Rey, 2020). The GFC is also closely correlated with global capital flows, where common factors, including key crisis events and changes to global liquidity and risk, significantly affect capital flows (Calvo et al., 1996; Forbes and Warnock, 2012; Fratzscher, 2012).

Monetary policy, particularly that of the US, plays a significant role in the GFC. Unconventional US monetary policy after the global financial crisis significantly impacts global financial conditions (Miranda-Agrippino and Rey, 2020; Rogers et al., 2018). The transmission of monetary policy also varies globally, with US monetary policy shocks affecting the global economy primarily through their effects on integrated financial markets, global asset prices, and capital flows (Farhi and Maggiori, 2018; Miranda-Agrippino and Nenova 2022; Miranda-Agrippino et al., 2020). Although US monetary policy shocks have a larger impact than those of the European Central Bank (ECB) on global financial markets and real activity, the role of the ECB as a driver of the GFC became more important after the global financial crisis (Ca' Zorzi et al., 2020; Miranda-Agrippino and Nenova 2022).

Furthermore, the US dollar, which remains the world's dominant anchor currency, plays a significant role in international financial markets (Gopinath, 2016; Gourinchas et al., 2019; Ilzetzki et al., 2019). Recent studies show that it plays a pivotal role in global financial market booms and busts (Akinci et al. 2022; Fuki et al., 2023; Obstfeld and Zhou, 2023). Notably, Obstfeld and Zhou (2023) find that the nominal exchange rate of the US dollar is closely associated with global financial conditions, even after controlling for standard determinants, such as monetary policy and domestic financial conditions in the US.

In summary, the GFC plays a significant role in the global economy by inducing a high degree of co-movement in asset prices, commodity prices, and capital flows across the globe. This co-movement, including that of exchange rates, appears to be driven by a few common global factors.

2. 2 Classifying Exchange Rate Regimes

The classification of exchange rate regimes has been a topic of interest, particularly after the end of Bretton Woods in the early 1970s. Since then, countries have employed divergent approaches for exchange rate management, ranging from continued adjustable pegs to freely floating exchange rates (Ghosh et al., 2003).

The divergence between policy and practice became evident in the mid-1990s. Obstfeld and Rogoff (1995) noted that countries claiming to have pegged their currencies often failed to maintain the fixed rates. Calvo and Reinhart (2002) argued that developing countries tended to manage their exchange rates more tightly than their officially claimed exchange rate system would imply, a phenomenon known as "fear of floating." These observations led to a new generation of classification methods, based on *de facto* practices for exchange rate management, most notably by Levy-Yeyati and Sturzenegger (2003, 2005), Reinhart and Rogoff (2004), and Shambaugh (2004).

A notable feature of these methods is their focus on actual exchange rate movements as classification inputs. Levy-Yeyati and Sturzenegger (2003, 2005), henceforth, LYS, examined the change and volatility of exchange rates, combining this information with variations in central bank reserves to determine whether a country uses pegged or flexible exchange rates, or an intermediate regime. Reinhart and Rogoff (2004) and Shambaugh (2004) used month-on-month variations in exchange rates as their main input for classification. Additionally, second-generation exchange rate regime classifications have been updated, with Levy-Yeyati and Sturzenegger (2016) updating LYS's, Ilzetzki et al. (2019) updating Reinhart and Rogoff's (2004) classification, and Klein and Shambaugh (2010) and Obstfeld et al. (2010) updating Shambaugh's (2004) classification. Ilzetzki et al. (2019), henceforth IRR19, proposed an algorithm that jointly classifies exchange rate arrangements and the anchor currency to which each currency is tied.

Our proposed approach is consistent with this new-generation classification method. A novel aspect of our approach is its focus on the common factors underlying actual exchange rate movements. This is motivated by recent literature on the GFC which indicates that a significant extent of exchange rate movements can be explained by a small number of common global factors.

3 Empirical Methods

3.1 Multivariate factor SV model

In accordance with Kastner et al. (2017), Kastner (2019), and Hosszejni and Kastner (2021), the multivariate factor SV model is defined as:

$$y_t|\Lambda,\ f_t,\ V_t \sim Normal(\Lambda f_t,\ V_t), \tag{1}$$

$$f_t|U_t \sim Normal(0,\ U_t), \tag{2}$$

$$V_t = diag(e^{h_{1t}}, \ldots, e^{h_{nt}}), \tag{3}$$

$$U_t = diag(e^{h_{n+1,t}}, \ldots, e^{h_{n+m,t}}), \tag{4}$$

where $y_t = (y_{1t}, \ldots, y_{nt})^T$ is the vector of observations, $\Lambda \in R^{n \times m}$ is a factor loading matrix, $f_t = (f_{1t}, \ldots, f_{mt})^T$ is the vector of factors, V_t is a matrix whose diagonal elements are series-specific variances, and U_t is a matrix whose diagonal elements are factor variances. The logarithm of variance follows an independent univariate stochastic volatility process:

$$h_{1t} = (1-\phi_i)\mu_i + \phi_i h_{i,t-1} + \sigma_i \eta_{it}, \quad i = 1, \ldots, n, \tag{5}$$

$$h_{n+j,t} = \phi_{n+j} h_{n+j,t-1} + \sigma_{n+j} \eta_{n+j,t}, \quad j = 1, \ldots, m, \tag{6}$$

where $\eta_t = (\eta_{1t}, \ldots, \eta_{n+m,t})^T$ denotes independent and normally distributed disturbances. The dynamic conditional covariance matrix of y_t is defined as $\Sigma_t = Cov(y_t|h_t) = \Lambda U_t \Lambda^T + V_t$.

The proportions of variance accounted for by the latent factors for each series are referred to as communalities, which are provided by

$$C_{it}=1-V_{ii,t}\Big/\Sigma_{ii,t},\ i=1,\ldots,n, \tag{7}$$

where $V_{ii,t}$ and $\Sigma_{ii,t}$ indicate the ith diagonal element of V_t and Σ_t, respectively. The overall communality, which is the mean over all series, is denoted by:

$$C_t=\Sigma_{i=1}^{n}C_{it}/n \tag{8}$$

The multivariate factor SV model was estimated using the Bayesian Markov chain Monte Carlo (MCMC) method. The details of the MCMC sampling steps are described by Kastner et al. (2017) and Kastner (2019)[1]. A hierarchical prior structure of the normal-gamma distribution was employed to shrink the unimportant elements of the factor-loading matrix to zero:

$$\Lambda_{ij}|\tau_{ij}^2\sim\mathrm{Normal}\ (0,\tau_{ij}^2),\ \tau_{ij}^2|\lambda_i^2\sim Gamma\left(a_i,\frac{a_i\lambda_i^2}{2}\right),\ \lambda_i^2\sim Gamma(c_i,d_i). \tag{9}$$

The priors for the log-variance processes are provided by $\mu_i\sim Normal(b_\mu, B_\mu)$, $(\phi_i+1)/2\sim Beta(a_0,b_0)$, and $\sigma_i^2\sim B_\sigma\chi_1^2=Gamma(1/2,1/2B_\sigma)$. The values of the prior hyperparameters were selected according to Kastner (2019)[2].

3.2 *K*-means and hierarchical clustering

We used the factor loadings, estimated by the multivariate factor SV model, to extract the behavioral features of gold and the 30 major currencies. We applied clustering analyses to the vectors of factor loadings and partitioned the 31 series into a small number of distinct homogenous clusters. Thus, the observations within each cluster were quite similar, whereas those in different clusters were quite different. Pairwise dissimilarities were measured using Euclidean distance. We employed two standard clustering methods: *K*-means and hierarchical clustering. To perform *K*-means clustering, the number of clusters must be specified in advance. We selected the optimal number of clusters, using three alternative methods: the within-cluster sum of squares (WCSS), average silhouette, and gap statistics[3]. Hierarchical clustering is an alternative method that is considered advantageous over *K*-means clustering because it does not require the number of clusters to be pre-specified. Furthermore, it visualizes the results as a graphical representation of a hierarchical cluster tree called a dendrogram, allowing us to investigate the hierarchical structure of the clusters. Ward's method was used for hierarchical clustering analysis. To evaluate the statistical significance of each cluster, we estimated approximately unbiased (AU) p-values, as proposed by Suzuki and Shimodaira (2006)[4].

3. 3 Data

Our sample includes the daily log returns of gold prices and exchange rates of the 30 major currencies. Special drawing rights (SDR) are used as a unit to measure these prices and exchange rates. The sample period is October 1, 2016, to July 31, 2022, during which time the currency shares of the SDR basket were fixed. Chinese renminbi were added to the basket on October 1, 2016. Table 1 presents summary statistics. The data were sourced from Foreign Exchange Rates, published by Exchange Data International.

Table 1

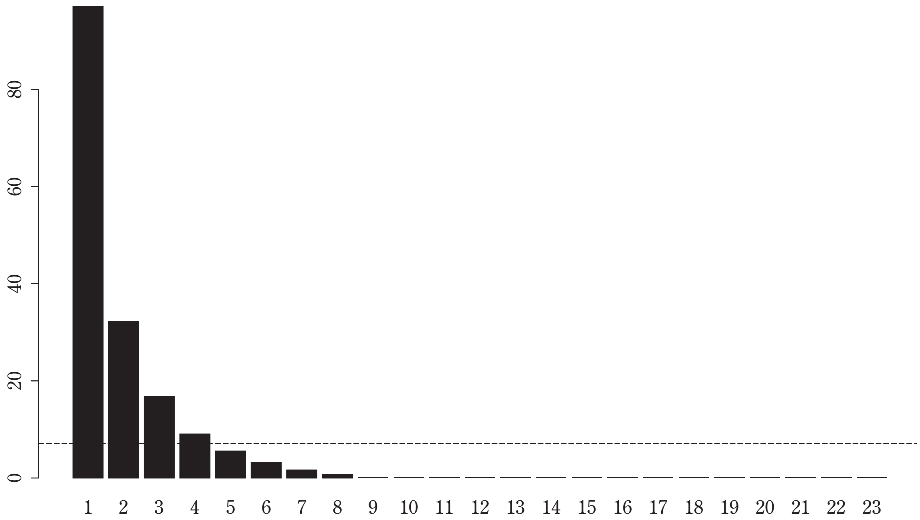
Currency	Code	Observations	Mean	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	ADF Test	
									Statisitics	*P*-value
Austrailian Dollar	AUD	1514	0.000	0.050	−0.064	0.006	−0.301	14.875	−10.481	0.000
Brazilian Real	BRL	1514	0.000	0.054	−0.085	0.010	−0.462	8.421	−9.660	0.000
Canadian Dollar	CAD	1514	0.000	0.022	−0.024	0.004	−0.012	4.931	−11.437	0.000
Swiss Franc	CHF	1514	0.000	0.029	−0.017	0.004	0.187	6.213	−11.758	0.000
Chilean Peso	CLP	1514	0.000	0.100	−0.040	0.008	1.286	20.990	−10.524	0.000
Chinese Renminbi	CNY	1514	0.000	0.017	−0.018	0.003	−0.227	7.302	−10.343	0.000
Czech Koruna	CZK	1514	0.000	0.025	−0.034	0.005	−0.395	6.672	−10.846	0.000
Danish Krone	DKK	1514	0.000	0.015	−0.023	0.004	−0.215	4.531	−12.457	0.000
Euro	EUR	1514	0.000	0.015	−0.023	0.004	−0.253	4.600	−12.514	0.000
British Pound	GBP	1514	0.000	0.034	−0.046	0.005	−0.267	8.466	−11.631	0.000
Hong Kong Dollar	HKD	1514	0.000	0.010	−0.007	0.002	0.281	5.299	−11.080	0.000
Hungarian Forint	HUF	1514	0.000	0.042	−0.035	0.006	−0.206	7.270	−11.816	0.000
Indonesian Rupiah	IDR	1514	0.000	0.078	−0.111	0.006	−3.320	112.905	−8.653	0.000
New Israeli Sheqel	ILS	1514	0.000	0.039	−0.035	0.005	−0.096	13.238	−10.661	0.000
Indian Rupee	INR	1514	0.000	0.016	−0.017	0.004	−0.088	4.339	−10.554	0.000
Japanese Yen	JPY	1514	0.000	0.028	−0.026	0.005	0.172	5.945	−10.662	0.000
Korean Won	KRW	1514	0.000	0.042	−0.036	0.005	0.194	8.989	−12.942	0.000
Mexican Peso	MXN	1514	0.000	0.042	−0.091	0.009	−1.240	15.982	−9.663	0.000
Norwegian Krone	NOK	1514	0.000	0.067	−0.116	0.008	−2.101	44.327	−11.323	0.000
New Zealand Dollar	NZD	1514	0.000	0.038	−0.060	0.006	−0.418	10.474	−10.933	0.000
Polish Zloty	PLN	1514	0.000	0.035	−0.034	0.006	−0.390	6.173	−12.386	0.000
New Romanian Leu	RON	1514	0.000	0.015	−0.023	0.004	−0.194	4.350	−12.737	0.000
Russian Ruble	RUB	1514	0.000	0.130	−0.227	0.016	−3.015	61.065	−9.857	0.000
Swedish Krona	SEK	1514	0.000	0.023	−0.045	0.006	−0.307	6.536	−11.518	0.000
Singapore Dollar	SGD	1514	0.000	0.015	−0.013	0.003	−0.047	4.733	−11.989	0.000
Thai Baht	THB	1514	0.000	0.012	−0.014	0.004	−0.056	3.858	−10.497	0.000
Turkish Lira	TRY	1514	−0.001	0.333	−0.176	0.015	5.834	189.436	−9.799	0.000
New Taiwan Dollar	TWD	1514	0.000	0.014	−0.012	0.003	0.033	4.835	−11.719	0.000
US Dollar	USD	1514	0.000	0.011	−0.007	0.002	0.266	5.276	−11.428	0.000
South African Rand	ZAR	1514	0.000	0.076	−0.070	0.010	−0.334	8.080	−11.178	0.000
Gold		1514	0.000	0.076	−0.071	0.009	−0.393	13.543	−10.616	0.000

Note: ADF: Augumented Dickey-Fuller

4 **Results**

We first fitted the model with twenty-three latent factors, indicated by the Ledermann bound (Ledermann, 1937) as the maximum possible number of factors. We then assessed the relative importance of each factor to explain the variance of the individual series based on the eigenvalues of the factor loading matrix. Figure 1 plots these eigenvalues, indicating that a sufficiently large proportion of the variance can be explained by four factors. Hence, we re-estimated the model using four factors.

Figure 1. Factors and Eigenvalues

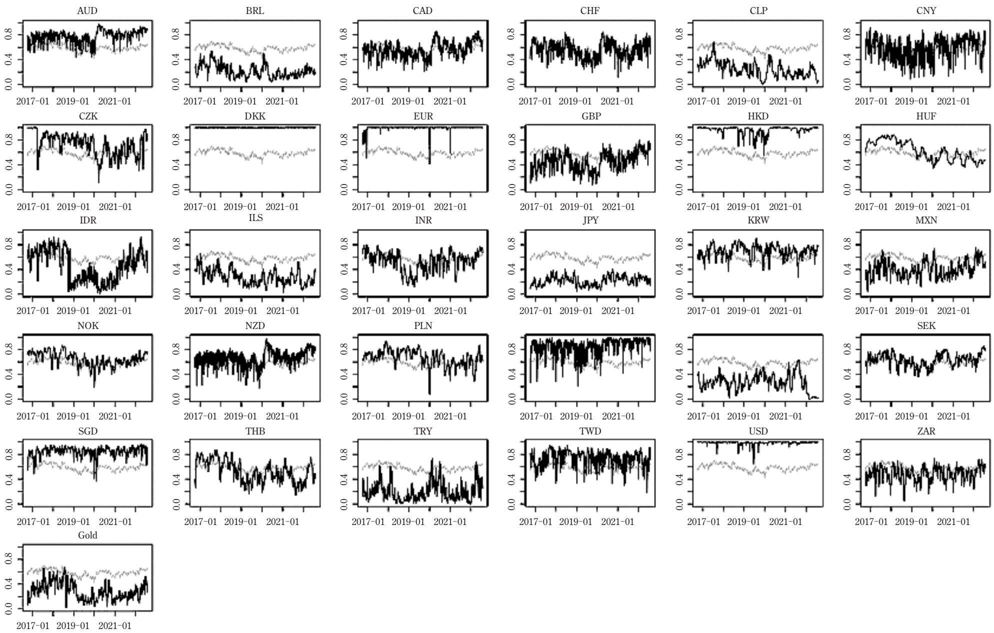


Note: The dotted horizontal line indicates the average of all eigenvalues.

Figure 2 shows the communalities of each series, along with the overall communality denoted by the dotted line. Remarkably, the communalities of the USD and EUR is nearly one almost throughout the sample period, suggesting that most of the variance in these currencies can be accounted for by these factors. The level of communalities remains high throughout the period for the HKD and DKK, which are effectively pegged to the USD and EUR, respectively.

Next, we applied *K*-means and hierarchical clustering to partition the 31 series into clusters according to their behavioral features, as captured by four-dimensional factor loadings. The optimal number of clusters was selected using three methods: WCSS, average silhouette, and gap statistics. Figure 3 presents the results, which unambiguously indicate that there are three optimal clusters. Therefore, we applied *K*-means clustering to partition the series into three distinct clusters, as shown in the first column of Table 2. The first cluster contains 11 currencies: the USD, eight Asian currencies, the ILS, and the TRY. This cluster can be labeled the USD block primarily because the USD is known to have long served as an anchor currency for Asian currencies (McKinnon, 2005). Although exchange rate systems became more flexible after the financial crisis of 1997–98, the results indicate that the USD continues to provide an anchor for

Figure 2. Communalities



Asian exchange rate systems. The second cluster contains nine currencies: the EUR and eight European currencies. The cluster can be labeled the EUR block because it consists of the currencies of the Eurozone and its peripheral countries. The third cluster is composed of gold and ten currencies, mainly commodity exporters. Accordingly, this cluster can be labeled a commodity currency block. A notable exception is the KRW, as Korea's largest exports are semiconductor products. The factor loadings for each series are shown in Figure 4. The colors, red, blue, and green were assigned to Clusters 1, 2, and 3, respectively. Figure 4 indicates that Factor 1 is the main driving force for the EUR block currencies because it loads positively on these currencies and negatively on the USD block currencies. Conversely, Factor 3 loads positively on USD block currencies and negatively on EUR block currencies, indicating that it is the main driving force of the former. Factors 2 and 3 load positively onto most commodity currencies, indicating that they are the primary driving forces of the third currency cluster.

Finally, hierarchical clustering was applied to obtain the dendrogram shown in Figure 5. A cluster with the AU p-value equals to or greater than 80% is denoted by a dot-dash line rectangle, indicating a relatively high level of statistical significance. A cut at a height of 6, indicated by the horizontal dotted line, suggests that there are three distinct clusters. The existence of these three clusters is also supported by the WCSS, average silhouette, and gap statistics, as

Figure 3. Optimal Number of Clusters for *K*-means Clustering

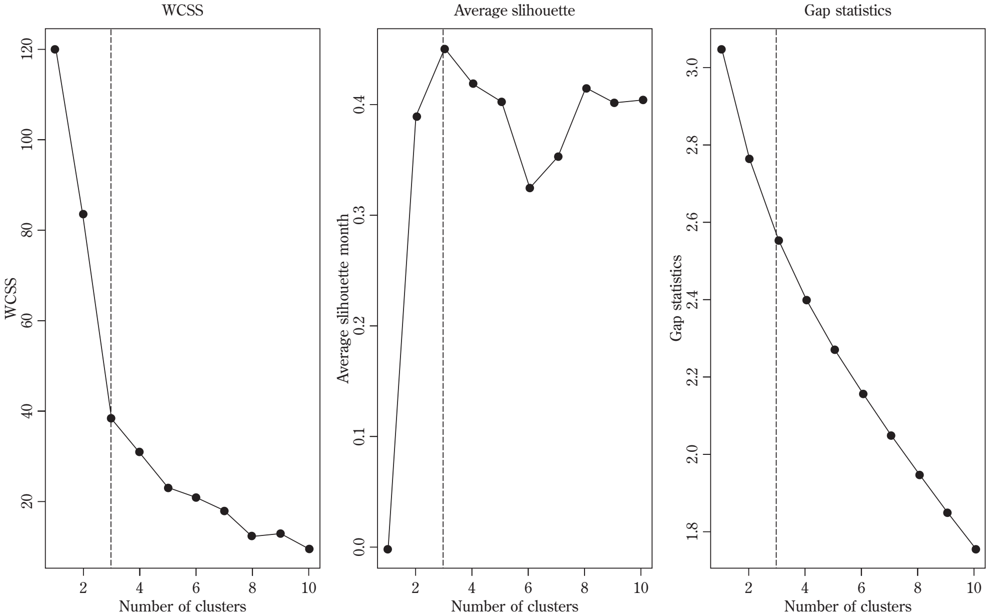
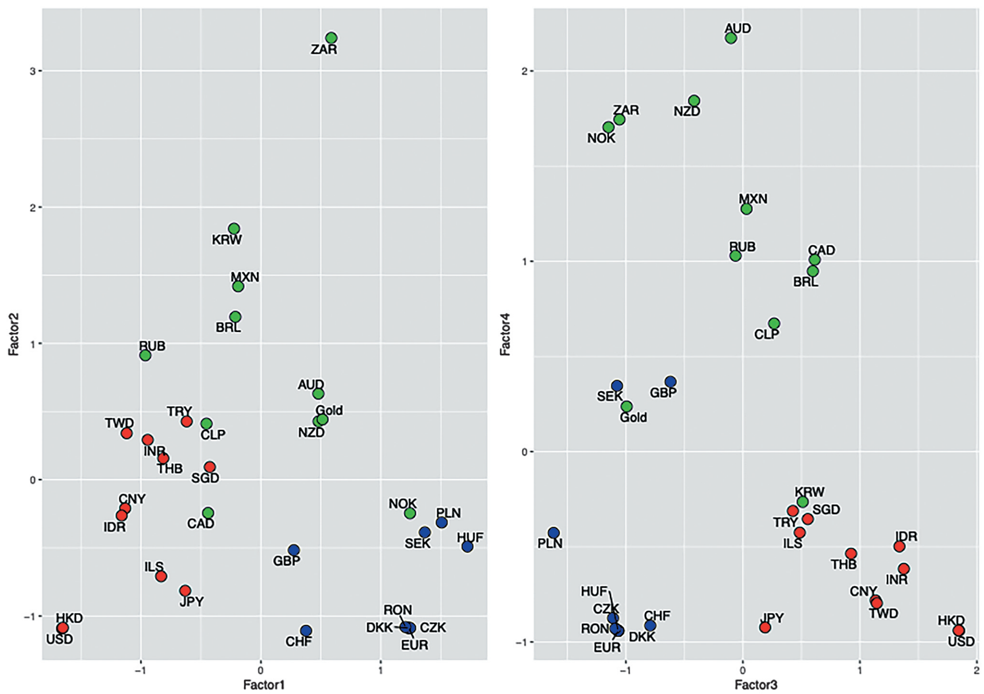


Figure 4. *K*-means Clustering and Factor Loadings

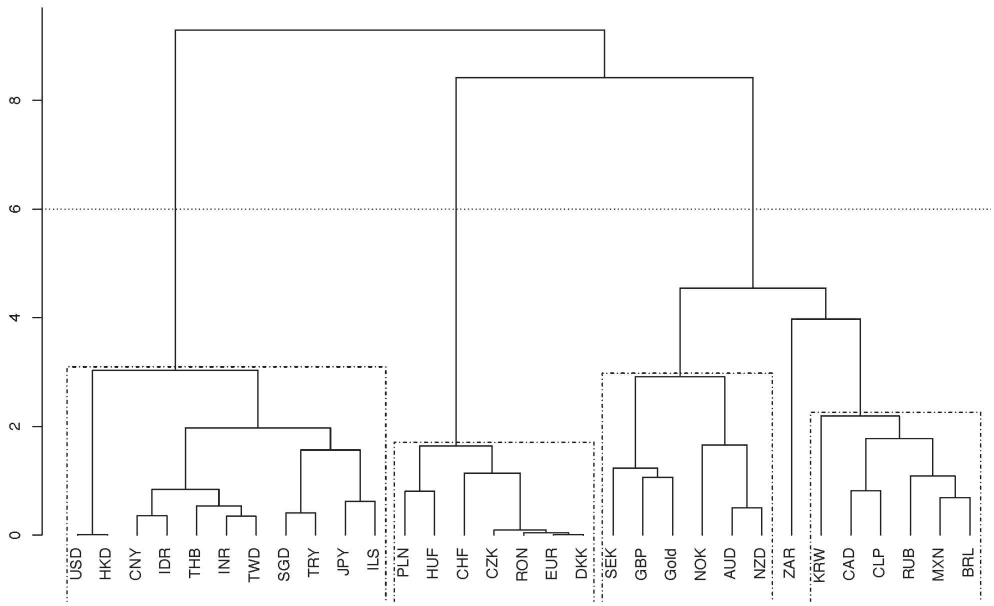


Note: Red, blue, and green are assigned to the series of clusters 1, 2, and 3, respectively.

Table 2

	K-means Clustering	Hierarichal Clustering
Cluster 1	CNY, HKD, IDR, ILS, INR, JPY, SGD, THB, TRY, TWD, USD	CNY, HKD, IDR, ILS, INR, JPY, SGD, THB, TRY, TWD, USD
Cluster 2	CHF, CZK, DKK, EUR, GBP, HUF, PLN, RON, SEK	CHF, CZK, DKK, EUR, HUF, PLN, RON
Cluster 3	AUD, BRL, CAD, CLP, KRW, MXN, NOK, NZD, RUB, ZAR, Gold	AUD, BRL, CAD, CLP, GBP, KRW, MXN, NOK, NZD, RUB, SEK, ZAR, Gold

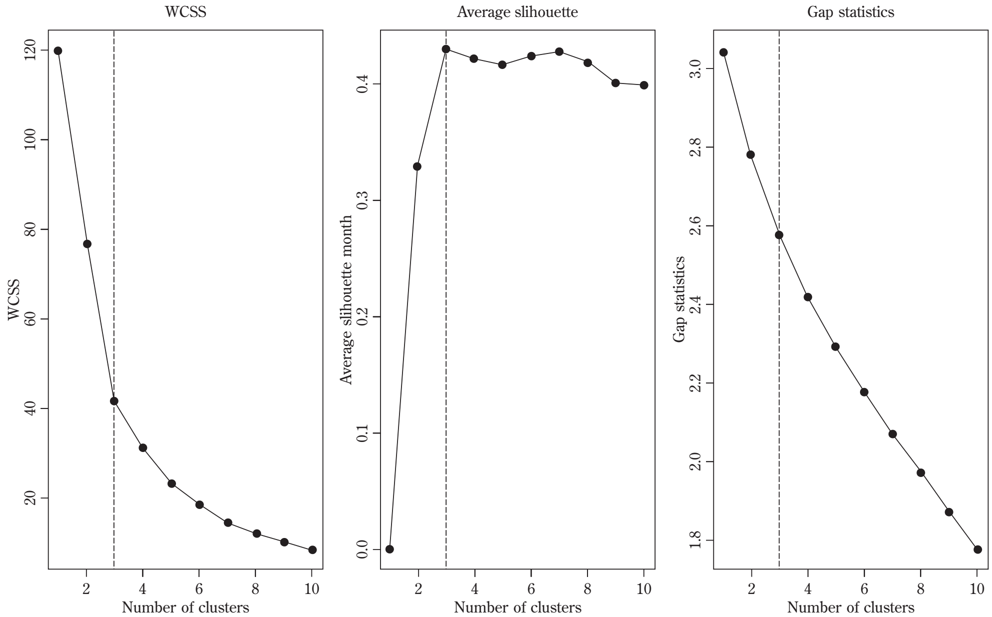
Figure 5. Dendrogram



Note: AU *p*-values equal to or greater than 80% are indicated by dot-dash line rectangles. A cut at a height of 6 is indicated by a horizontal dotted line.

shown in Figure 6. The resulting clusters are summarized in the second column of Table 2. The first cluster consists of the same currencies as the USD block derived from *K*-means clustering. The second cluster contains most currencies in the EUR block based on *K*-means clustering, with the exception of GBP and SEK. The third cluster consists of gold and the same currencies as in the commodity currency blocks of *K*-means clustering. It also includes GBP and SEK, which are classified into EUR blocks based on *K*-means clustering. However, the *p*-value for the entire cluster was not very high. A relatively high *p*-value of greater than 80% was observed for two subclusters : the first contained SEK, GBP, gold, NOK, AUD, and NZD, and the second contained KRW, CAD, CLP, RUB, MXN, and BRL. The only currency that belongs to

Figure 6. Optimal Number of Clusters for Hierarchical Clustering



neither group is the ZAR, which is the only African currency in the sample.

5 Conclusions

In this study, we propose a novel approach for categorizing global currencies. This approach is based on identifying the shared driving forces that shape the behavioral characteristics of these currencies. This is motivated by recent literature on the GFC, which indicates that a significant extent of exchange rate movements can be explained by a small number of common global factors. We utilized a sophisticated statistical tool, the multivariate factor Stochastic Volatility (SV) model, to identify common factors that are not directly observable but significantly influence currency behavior.

Our methodology involves applying two well-established clustering techniques, *K*-means and hierarchical clustering, to the factor loadings estimated by the SV model. Through this rigorous analysis, we identified three distinct currency clusters. These clusters, which we label the USD, EUR, and commodity currency blocks, exhibit unique behavioral patterns and are influenced by different economic factors.

Interestingly, our hierarchical clustering results further suggest that commodity currency blocks can be subdivided into two statistically significant subclusters. This finding adds a layer of complexity to our understanding of currency behavior.

We believe that our novel approach to currency classification is of immense value to various stakeholders, including investors and policymakers. It enables them to better evaluate the risks associated with different currencies. As our study shows, while these risks are shared within the same currency block, they vary significantly between different blocks. Hence, our approach provides a nuanced understanding of currency risks, which is crucial for effective decision making in the global financial market.

Notes

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1) We use the R package “factorstochvol” (Hosszejni and Kastner, 2021) for estimation.
2) See Kastner et al. (2017), Kastner (2019), and Hosszejni and Kastner (2021) for details.
3) We use the R package “factoextral” for implementing these methods.
4) We use the R package “pvclust” for estimating the *p*-values of clusters.

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