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Financial Data Science

Dynamic Analysis of Currency Networks: Centrality, Baskets, and Variability Metrics

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Abstract

The aim of this paper is to develop a stablecoin based on a basket of carefully selected currencies, employing two distinct approaches: the Minimum Variance method and Centrality-based methods. We aim to compare the performance of these approaches by determining the optimal weights for the selected currencies and fine-tuning relevant hyperparameters to improve the results. To facilitate this comparison, we introduce specific performance metrics to evaluate the stability and resilience of each method as a financial instrument. Finally, we analyze the advantages and disadvantages of adopting one method over the other as a replacement for individual currencies in the global market.

1. Introduction

1.1 What is a Stablecoin?

A stablecoin is a type of digital currency designed to maintain a stable and consistent value, making it suitable for everyday transactions and financial activities. This stability has led to a growing interest in stablecoins, which have become a widely discussed subject. In fact, companies such as Meta are exploring and developing their own versions of stablecoins, recognizing the strategic advantages of relying on currencies that do not fluctuate excessively.

A key innovation of stablecoins is directly correlated to how they are built: by converting a basket of selected currencies into this new digital asset, we achieve a minimization of basket volatility. This approach is far superior to normalizing with respect to a single currency, which remains vulnerable to fluctuations. Diversification of currencies within the basket ensures systematic movement over time, where depreciation in one currency can be balanced by appreciation in another. The balancing effect of this diversification enhances stability and reduces variance in value.

Beyond their role as variance-reduction tools, stablecoins offer utility as direct substitutes for cash, similar to electronic money. Their stable nature makes them well-suited for use in transactions, payments, and savings, bridging the gap between traditional fiat currencies and digital assets.

In summary, stablecoins represent a promising innovation for achieving financial stability and resilience in the digital economy. By exploiting diversification across a basket of hard currencies, they minimize fluctuations and offer robust protection against currency shocks.

1.2 Why Stablecoin?

The pursuit of a stablecoin is justified in light of a global economic context characterized by recurring financial crises and the growing demand for international trade activities. Over the past decades, the instability of currencies has become increasingly evident, particularly during major disruptive events such as the 2008 global financial crisis and, more recently, the COVID-19 pandemic. These crises have not only exposed the fragility of the global financial system but also highlighted its inability to ensure stability and resilience under adverse conditions.

In this context, a digital currency emerges as a viable alternative capable of alleviating these issues by reducing the risks of devaluation.

Furthermore, the rapid acceleration of globalization and digitalization has intensified the need for efficient, trustworthy, and secure financial instruments that can keep pace with the growing complexity of international trade networks. Finally, stablecoins represent an innovative solution for international transactions by promoting greater economic integration between emerging and advanced economies.

1.3 BRICS+

In constructing our stablecoin, we decided to include some currencies from emerging economies, specifically Brazil, Russia, India, China, South Africa, Iran, Egypt, Ethiopia and the United Arab Emirates collectively known as the BRICS+ nations (with the last four entered this year). This choice is guided by the significant influence these countries have gained on the global economy: according to the World Economic Outlook (IMF) (April 2024), these countries collectively contribute around 35% of the global GDP (in terms of purchasing power parity (PPP)), and their importance continues to grow. Their sustained economic expansion, vast natural resources, and increasing financial and commercial influence are key indicators of this rising importance.
Therefore, in the future, BRICS+ could become a serious competitor to more traditional currencies, such as the US dollar and the Euro, increasingly reducing their dominance in the global market.

For these reasons, BRICS+ nations make a natural and inevitable choice for inclusion in the stablecoin's currency basket alongside traditional currencies.

1.4 Our Stablecoin

The introduction of a new stablecoin, built on a basket of currencies that includes those of BRICS (before 2011) nations and other significant global economies, represents a well-founded solution and could provide several advantages:

- By combining emerging market currencies with established ones, the system reduces dependence on any single economy, allowing for a more balanced and reliable value foundation. This occurs because the stablecoin is constructed on a diversified basket of currencies, including those of BRICS (Brazil, Russia, India, China, South Africa), the Australian dollar, the Euro, the Japanese Yen, and others.
- Diversification minimizes the impact of economic fluctuations. If one economy or currency within the basket shows instability, the others serve as stabilizing factors, providing protection against volatility and potential economic crises.
- The stablecoin could remove barriers to global trade between BRICS+ nations and other markets by minimizing currency conversion costs and exchange rate risk, enabling a more inclusive and interconnected financial ecosystem.
- The currency provides an alternative that is less exposed to the monetary policies or economic decisions of individual states. It mitigates the risks of sudden devaluations or inflationary pressures, offering a more neutral and resilient financial instrument.

2. Literature

In this section, we examine the existing literature on stablecoin mechanisms, portfolio optimization methods, and the role of emerging market currencies, particularly focusing on the BRICS+ nations.

2.1 Minimum Variance Method

The construction of stablecoins based on a basket of currencies aligns closely with principles from portfolio optimization theory. Markowitz's Modern Portfolio Theory (MPT) provides the foundational framework for minimizing risk through diversification. The Minimum Variance approach, a key extension of MPT, focuses on determining optimal weights for assets in a portfolio to achieve the lowest variance.

Existing studies have applied portfolio optimization techniques to currency baskets to mitigate exchange rate volatility, like Giudici libra (2022)[1] and Hovanov et al.(2004)[2]. However, while some approaches have been extensively studied for traditional currency portfolios, the use of emerging market currencies, which exhibit higher volatility, remains underexplored.

2.2 The Role of BRICS+

The inclusion of emerging market currencies, particularly those from Brazil, Russia, India, China, and South Africa (BRICS), in stablecoin baskets has garnered increasing attention due to their growing economic influence. According to the International Monetary Fund (IMF) World Economic Outlook (April 2024), BRICS+ nations collectively contribute approximately 35% of the global GDP, with their share expected to grow in the coming decades. Their rapid economic expansion, abundant natural resources, and increasing financial interconnectivity position them as key players in the global economy.

There are some diversification benefits of including emerging market currencies in financial portfolios, particularly during periods of economic uncertainty. There have been further highlights regarding the potential for BRICS+ currencies to reduce dependency on traditional reserve currencies, such as the US dollar and the Euro, thus mitigating risks associated with monetary policies of dominant economies.

Despite these benefits, challenges persist. Emerging market currencies are often more volatile and are subject to economic and geopolitical shocks. Therefore, designing a stablecoin that incorporates BRICS+ currencies requires balancing their growth potential with risk mitigation strategies to achieve stability.

2.3 Performance Metrics for Stablecoin Stability

Adopting stress testing and sensitivity analysis to evaluate stablecoin behavior under adverse market conditions are particularly relevant for comparing alternative approaches, such as the Minimum Variance and centrality-based methods, for constructing currency baskets. However, there remains a lack of consensus on standardized performance metrics specifically designed for stablecoins, presenting an opportunity for further research.

2.4 Research Gaps

Despite notable advancements in the study of stablecoin mechanisms and portfolio optimization strategies, several research gaps remain. First, there is a lack of extensive investigation into the integration of BRICS+ currencies within stablecoin baskets, even as these currencies continue to gain prominence in the global economy. Second, comparative studies between the Minimum Variance approach and alternative methodologies, such as centrality-based techniques, are relatively scarce. Finally, the development of standardized performance metrics for assessing the stability and resilience of basket-backed stablecoins remains limited.

This paper seeks to address these gaps by constructing a stablecoin composed of BRICS+ and traditional currencies, evaluating the performance of the Minimum Variance and centrality-based approaches, and proposing customized metrics to measure stability and resilience.

3. Methodology

In this section, we detail the methods utilized in our empirical analysis. Firstly, we will discuss the different approach that can be used to transform the input time series data to a more useful network representation. Next, we will explore the different centrality metrics that can be use to extract information about the cumulative behavior of the exchange rates. Then, we will analyze how the knowledge about the centrality can be expressed as weights to be used to define a basket of currencies that minimize variability. Lastly, we will explain the Min-var method as stated in Hovanov et al. (2004)[2].

3.1 Network construction

To build a network, starting from the forex time series data, we defined a *window* onto witch we estimated the correlation matrix R. Then, we transformed R to a distance matrix d (Eq. 3.1).

$$d = \sqrt{2\,(1 - R)} \tag{3.1}$$

Then, d is used as input to the *Minimum Spanning Tree* (MST) and the *Planar Maximally Filtered Graph* (PMFG) algorithms to create a graph onto witch calculate the different centrality measures that will be introduced in Section 3.2.

3.1.1 Minimum Spanning Tree

A Minimum Spanning Tree is a subgraph that connects all the nodes in a graph with the minimum total edge weight and no cycles. It identifies the most efficient way to link a set of points, minimizing overall costs such as distance or resources, and is widely used in network design and optimization.

3.1.2 Planar Maximally Filtered Graph

The Planar Maximally Filtered Graph is a network analysis method that extends the Minimum Spanning Tree by preserving more edges while ensuring planarity. It retains critical structural and hierarchical properties, making it useful for analyzing complex systems like financial or biological networks.

3.2 Centrality Measures

Centrality measures are fundamental tools in graph theory and network analysis. They help quantify the importance or influence of nodes in a graph based on their position and connections. In the context of our project, which analyzes the flow of stablecoins and currencies in the financial network, centrality measures are crucial for identifying the most influential nodes (e.g., currencies, exchanges, or market participants) that affect the stability and efficiency of currency flows.

A high centrality value often suggests that a node has a significant role in the network, but it may also imply that the node is less correlated with other nodes in the system. This is especially true for degree centrality, where nodes with higher degrees (more connections) might act as hubs, while other nodes may be more peripheral. However, in the case of closeness and betweenness centrality, higher values generally indicate that a node is strategically positioned to affect the flow of information or resources between other nodes, highlighting their importance in maintaining connectivity or facilitating transactions.

These measures allow us to assess the role of each currency or node within the broader network, shedding light on how central entities might influence the global financial system or the dynamics of arbitrage and liquidity in the stablecoin market.

In our project, we utilized five centrality measures—degree, closeness, betweenness, eigenvector, and PageRank—each providing unique insights into the network. Together, these measures offer a comprehensive understanding of the roles played by currencies and nodes in the financial network.

3.2.1 Degree Centrality

Degree centrality measures the importance of a node based on its number of connections. For a graph $G = (V, E)$ with node v, the degree centrality $C_D(v)$ is:

$$C_D(v) = \deg(v)$$

where $\deg(v)$ is the number of edges connected to v.

3.2.2 Closeness Centrality

Closeness centrality assesses how close a node is to all other nodes in the network. For a node v, it is defined as:

$$C_C(v) = \frac{1}{\sum_{u \in V} d(v, u)}$$

where $d(v, u)$ is the shortest path distance between nodes v and u.

3.2.3 Betweenness Centrality

Betweenness centrality measures the extent to which a node lies on the shortest paths between other nodes. For a node v, it is given by:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths that pass through v.

3.2.4 Eigenvector Centrality

Eigenvector centrality assigns importance to nodes based on the principle that connections to highly connected nodes contribute more. For a node v, it is defined as:

$$C_E(v) = \frac{1}{\lambda} \sum_{u \in V} A_{uv} C_E(u)$$

where A is the adjacency matrix of the graph, λ is the largest eigenvalue, and $C_E(u)$ is the eigenvector centrality of node u.

3.2.5 PageRank

PageRank centrality is computed as:

$$C_{PR}(v) = \frac{1-d}{N} + d \sum_{u \in \mathrm{In}(v)} \frac{C_{PR}(u)}{\deg(u)}$$

where d is the damping factor (usually set to 0.85), N is the total number of nodes, and $\mathrm{In}(v)$ is the set of nodes pointing to v.

3.3 Transition from Centrality to Basket Weights

These centrality measures not only provide insights into the network's structure but also serve as the foundation for deriving the weights assigned to each currency in the basket, aiming for stability and balance. By normalizing the centralities c, we calculate weights w that sum to one:

$$w_i = \frac{c_i}{\sum_j c_j}$$

These weights represent the relative contribution of each currency within the basket, ensuring a proportionate and data-driven distribution.

3.3.1 Inverting Centralities to Preserve Meaning

For measures like closeness and betweenness, in witch the more correlated currencies are also the more central, it is important to consider an inverse of the measure to calculate the weights. Several transformation options can be used, with *Inverse* and *Inverse max* being particularly noteworthy:

Inverse adjusted

The centrality c is inverted to reflect importance directly:

$$c' = \frac{1}{c + \epsilon} \tag{3.2}$$

Here, ϵ is a small constant added to avoid division by zero.

Inverse Distance from Maximum

The centrality c is transformed by subtracting it from the maximum centrality value:

$$c' = \max(c) - c \tag{3.3}$$

This transformation reverses the scale, assigning higher values to nodes with lower original centrality.

Both transformations ensure that the weights derived from centralities retain the original meaning, with higher weights assigned to less correlated currencies.

3.4 Min-var

The Minimum Variance (Min-var) method is a key approach in the construction of currency baskets, aligning closely with the principles of Modern Portfolio Theory (MPT). Introduced by Markowitz, MPT emphasizes risk minimization through diversification, making Min-var a logical extension for financial applications. By assigning weights to currencies within a basket to achieve the lowest possible variance, this method prioritizes stability over return maximization.

Building on the work of Hovanov et al. (2004)[2], we apply the Min-var method to our dataset, which includes a diversified selection of currencies. This ensures that the basket is resilient to market shocks while maintaining low variance:

$$\mathrm{RNVAL}\left(\frac{t}{t_0}\right) = \frac{\frac{c_{ij}(t)}{\sqrt{\prod_{k=1}^{n} c_{kj}(t)}}}{\frac{c_{ij}(t_0)}{\sqrt{\prod_{k=1}^{n} c_{kj}(t_0)}}} = \sqrt[n]{\prod_{k=1}^{n} \frac{c_{ik}(t)}{c_{ik}(t_0)}} \tag{3.4}$$

where $c_{ij}(t)$ denotes the exchange rate between currencies i and j at time t, with $i, j = 1, \ldots, n$ (where n denotes the number of currencies).

By reducing to the moment t_0 and normalizing each currency observation by the geometric average of the other currencies at that specific point in time, the RNVAL allows the computation of a unique optimal, minimum variance currency basket, despite the base currency choice.

4. Data and Empirical Findings

In this current section, we are going to present and analyze the dataset used in our study, providing a detailed exploration of its characteristics and the insights derived from empirical findings.

Firstly, the data used are taken through a custom scraper that retrieves closing prices from Yahoo Finance. Closing prices are often used in financial modeling and technical analysis. Additionally, Yahoo Finance provides a comprehensive and consistent dataset for a wide range of financial instruments, making it a practical and accessible choice. Its global coverage ensures the availability of data for various markets, enhancing the versatility and scalability of the analysis.
Our dataset consists of daily exchange rates for a selection of currencies, normalized against the US Dollar (USD). These data span from mid-2006 to the present day (December 2024).
The following currencies are included:

- **BRICS+ Economies (pre-2011):**
  - Brazilian Real (BRL)
  - Russian Ruble (RUB)
  - Indian Rupee (INR)
  - Chinese Yuan (CNY)
  - South African Rand (ZAR)
- **Other Major Economies:**
  - Australian Dollar (AUD)
  - Swiss Franc (CHF)
  - Euro (EUR)
  - British Pound (GBP)
  - Japanese Yen (JPY)
  - Mexican Peso (MXN)
  - Nigerian Naira (NGN)
  - Philippine Peso (PHP)

4.1 Visualization of Raw Data

We started presenting the raw time series data for the currencies under consideration. This visualization highlights long-term trends and fluctuations in different currencies.

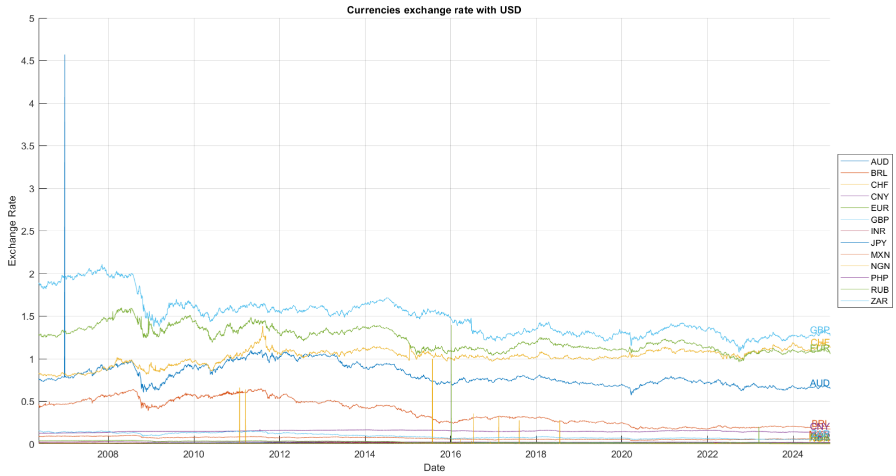


Figure 4.1: Raw exchange rate data used to compute metrics for stabilizing the currency basket.

From this figure we can notice that different currencies show different trends, for example, GBP, CHF, EUR, AUD and BRL seem to be more volatile than the others, this shows that the majority of the non-BRICS economies (with the exception of Brazil) have faced greater instabilities in the analyzed period, such as the 2008 crisis and the COVID-19 pandemic. We can also see some unwanted noise and confusing data, including, for example, the spike of the AUD in the first years shown in Figure 4.1. We expect that these behaviors are not shown in the metrics that we want to build, since the goal is to take a sort of weighted average of all the currencies in order to stabilize the basket. These patterns reflect not only local monetary policies but also global economic dynamics.

The next step is to analyze the daily returns for these currencies, as shown in Figure 4.2. This provides insights into their volatility and risk characteristics.

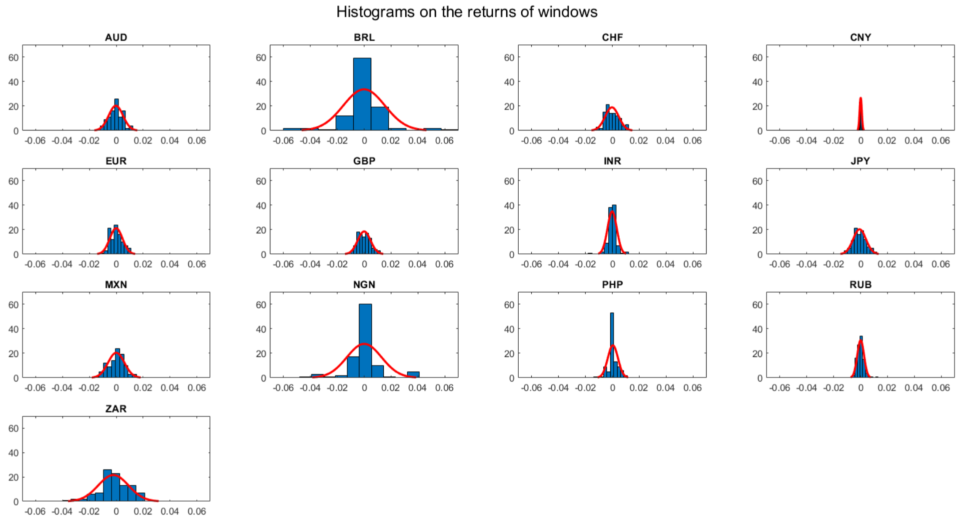
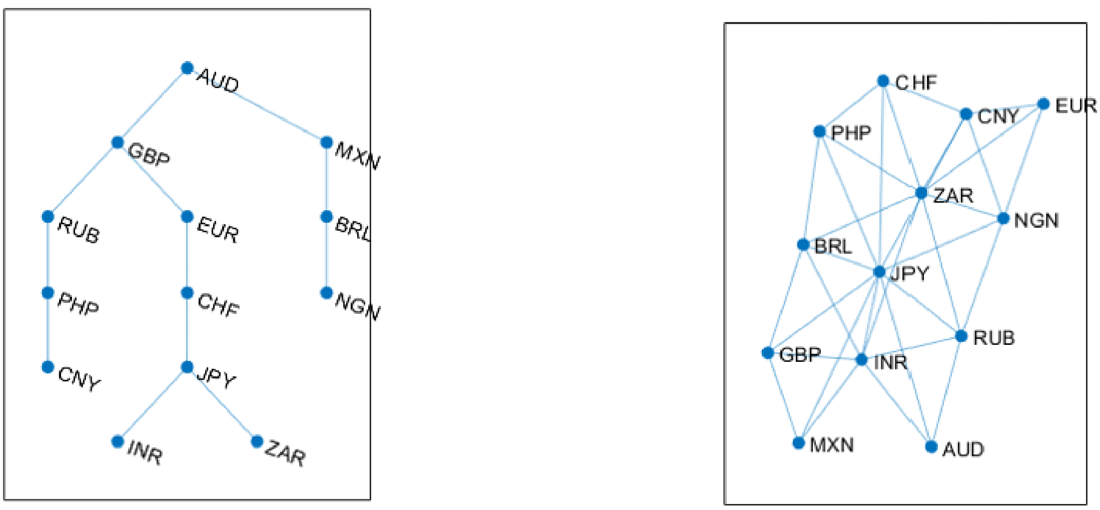


Figure 4.2: Distribution of daily returns for the currencies. We can observe that we have differences in the spread and shape of distributions that reflect varying levels of risk and return potential across currencies.

4.2 Graph Construction and Analysis

We have then computed the covariance matrix from the time series data using a rolling window (window size = 100, chosen from a random search of this hyperparameter, this value gives us the best results for our objective), and subsequently transformed it into a distance matrix, mapping the values from the interval $[-1, 1]$ to $[0, 2]$. From this we construct two key graph representations: the Minimum Spanning Tree (MST) and the Planar Maximally Filtered Graph (PMFG).



(a) MST (b) PMFG

Figure 4.3: Graph representations: MST and PMFG, highlighting structural differences despite being derived from the same metrics.

The construction of the MST and PMFG allowed us to capture meaningful relationships between currencies, eliminating unnecessary noise. It is also easy to see that these graphs bring us different information because, at least for the great majority of nodes, a central node in the MST corresponds to a non central node in the PMFG. The complementarity between MST and PMFG emerges clearly when considering less central nodes, which highlights the importance of using different graphical representations to achieve a more robust analysis.

Graph-based metrics (degree, betweenness, closeness, PageRank, eigenvector centralities) are computed to identify key nodes (currencies) and relationships within these networks.

We also have computed the Min-var method according to Hovanov et al. (2004)[2] to compare the two approaches against each other later on.

After that we have seen how the centrality metrics (so, Min-var excluded) appear on the graphs:

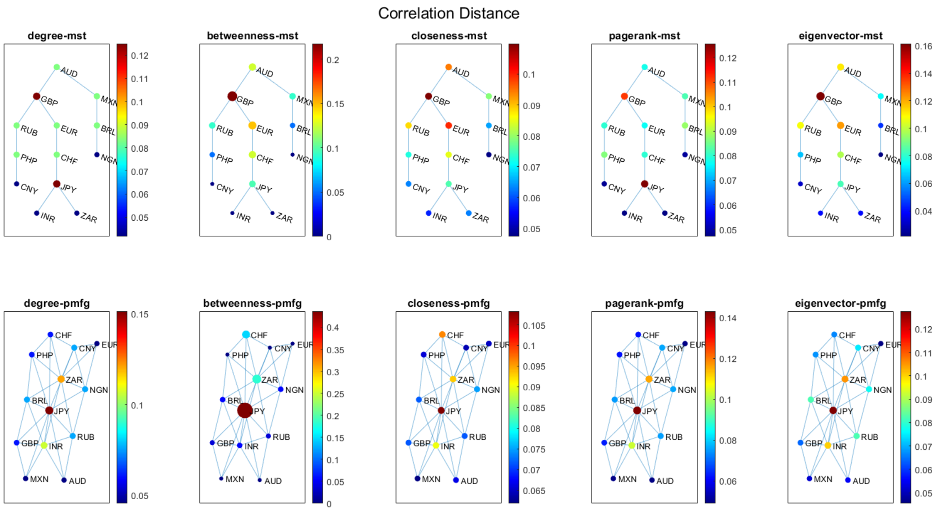


Figure 4.4: Different types of centralities applied either on the MST (Minimum Spanning Tree) and the PMFG (Planar Maximally Filtered Graph)

Figure 4.4 illustrates the graphical representation of the centrality metrics applied to the nodes of the Minimum Spanning Tree (MST) and the Planar Maximally Filtered Graph (PMFG). These visualizations provide a clear understanding of how centrality values are distributed across nodes, highlighting the most influential ones. This information is critical for identifying key connections and dependencies within the network structure, as well as for understanding the differences between the two types of graph representation.

4.3 Metric Adjustments

Certain centrality metrics, such as betweenness and closeness, are adjusted to emphasize less central nodes. This is done because the behavior of central nodes can be predicted by looking at their neighbours and so, for our objective, we are more interested in the less central nodes, since their behavior cannot be predicted as good as the central ones (because they have more incoming link, and this translate to a bigger amount of information correlated to them).

For the purpose of our project, we have opted to normalize betweenness and closeness centrality using the transformation:

$$c' = \max(c) - c \tag{4.1}$$

rather than the alternative:

$$c' = \frac{1}{c + \epsilon} \tag{4.2}$$

This choice is motivated by the specific goal of assigning greater weight to less central nodes within the network. While the reciprocal transformation emphasizes low centrality values by creating a more pronounced distinction among them, it also introduces a non-linear scaling that can affect the interpretation of centrality differences.
In contrast, the subtraction-based inversion retains the linear relationship between original values and their transformed counterparts, offering a more intuitive point of view for analysis while effectively inverting the scale.
This approach aligns better with our objective of emphasizing peripheral nodes without compromising the interpretability of the centrality measures.

4.4 Metric Characteristics and Analysis

In order to evaluate and understanding better the behavior of our results, we have computed some statistical metrics from our graphs. These metrics summarizes key statistical properties of the values computed in the MST and PMFG graphs.

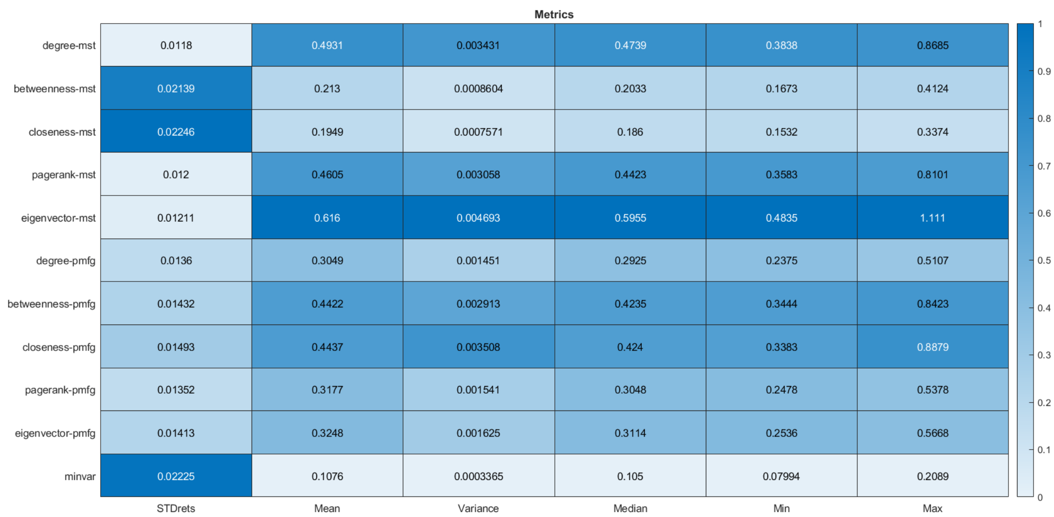


Figure 4.5: Metrics built on top of our 2 graphs representation (heatmap coloring highlights variability and distribution patterns).

As we can see the Min-var, as its name suggest, does a very good job at minimizing the variance of the time series, but it cannot obtain a very good value also in the standard returns. We can see better this behavior by looking at the next two figures.

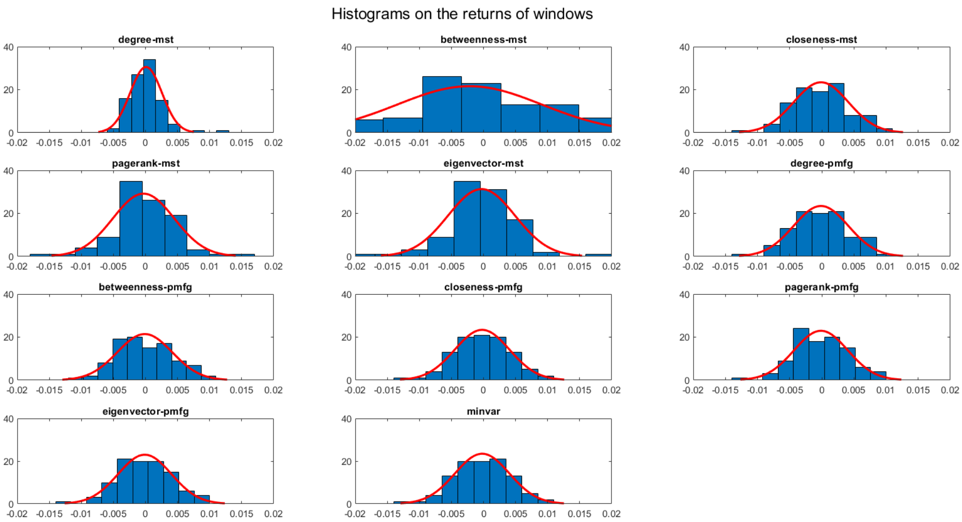


Figure 4.6: Returns of the metrics. Same scale shown to appreciate the differences between them.

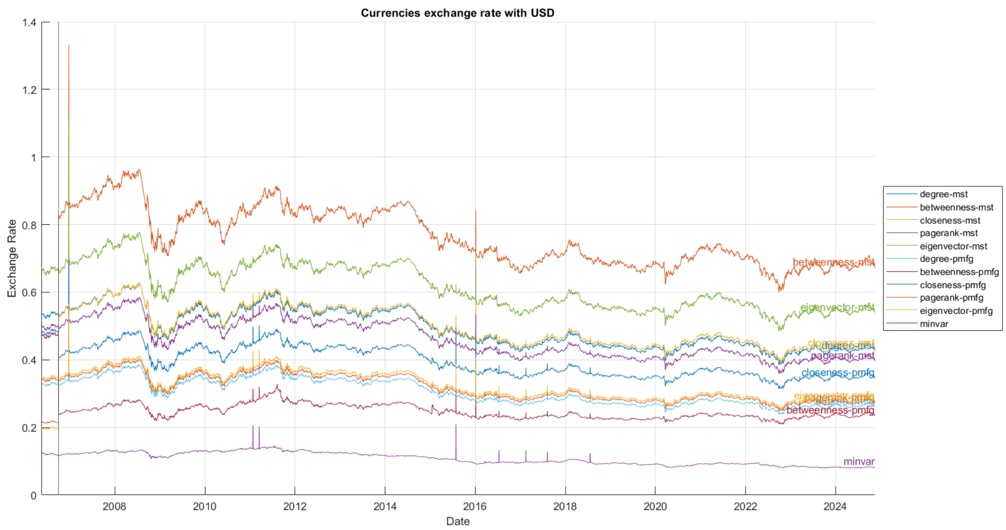


Figure 4.7: Time series of the metrics. All of them try to summarize the movement of the different currencies we have in our basket.

As highlighted in Figure 4.6, centrality-based metrics appear more effective at optimizing returns than purely variance-based metrics. The Min-var indeed sacrifices its performance in the returns for superior stability, this can be seen in Figure 4.7. This reflects a classic trade-off between stability and return: centrality-based metrics offer a more risk-oriented outlook, making them useful for strategies seeking to capitalize on currency fluctuations, while Min-var remains ideal for conservative strategies.

4.5 Stride

In this study, we employ also a stride-based methodology to optimize the weights of the portfolio over a rolling window. Specifically, the weights are recalculated every N days based on the available data up to that point. Once the optimal weights are determined, they remain fixed for the subsequent N days, during which we evaluate the performance of the time series. This approach allows us to capture temporal dynamics and assess the stability of the weights over multiple non-overlapping periods. By iterating this process across the dataset, we can analyze the robustness and consistency of the optimization strategy in varying market conditions. The stride length N represents a balance between frequent recalibration and minimizing transaction costs.

The previous images and all the reasoning before were done with the stride hyper-parameter set to infinite (this means without recomputing the weights), now instead we tried to see what could happen with the stride set to 500.

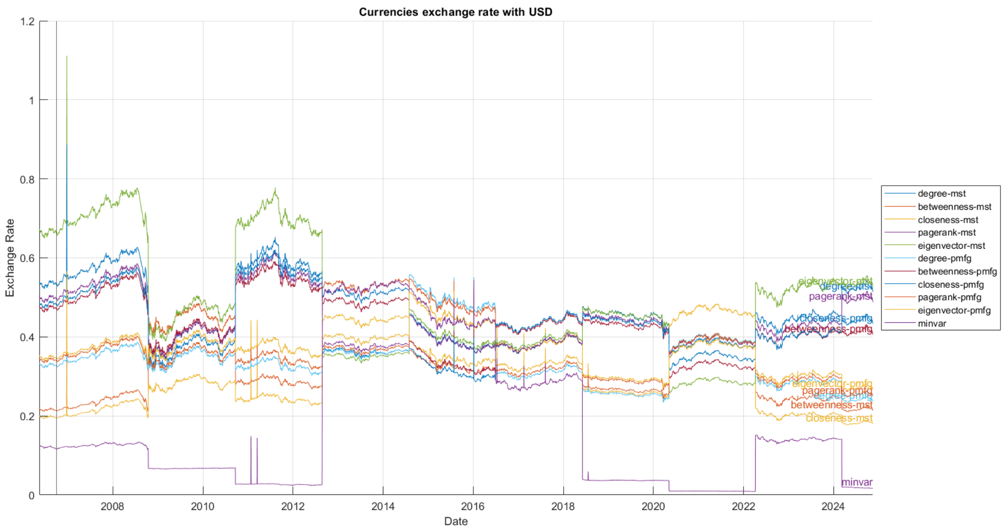
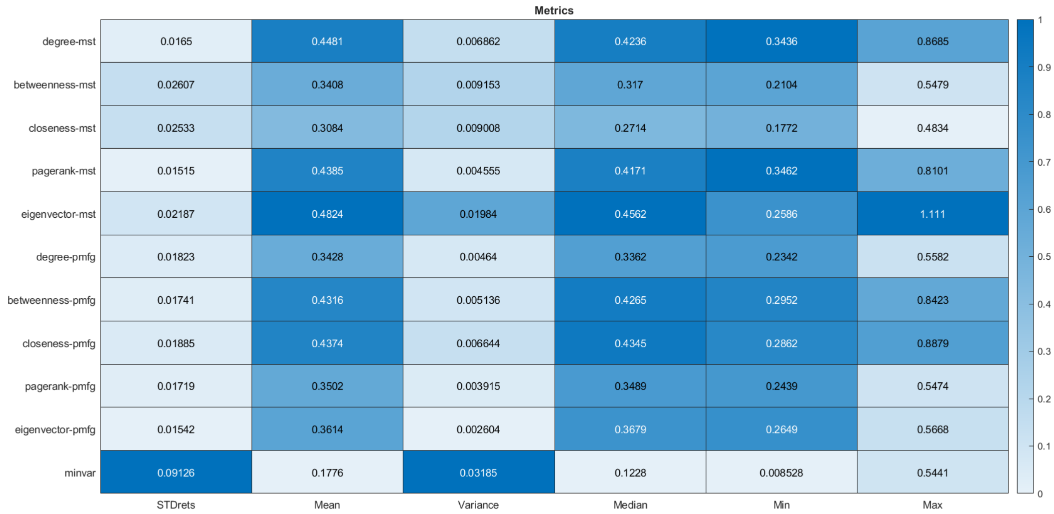


Figure 4.8: Here we can see that the weights, being recomputed after some days, will vary very much in different ways according to different periods: we can see a more stable period from 2013 to 2018, and other periods that shows steep changes, we can recognize the years around the 2008 crisis and around the COVID-19 pandemic.

In Figure 4.8 we can see how the Min-var struggles to keep low the stability of its time series, and this behavior can be seen by looking at the table:



Metrics

	STDrets	Mean	Variance	Median	Min	Max
degree-mst	0.0165	0.4481	0.006862	0.4236	0.3436	0.8685
betweenness-mst	0.02607	0.3408	0.009153	0.317	0.2104	0.5479
closeness-mst	0.02533	0.3084	0.009008	0.2714	0.1772	0.4834
pagerank-mst	0.01515	0.4385	0.004555	0.4171	0.3462	0.8101
eigenvector-mst	0.02187	0.4824	0.01984	0.4562	0.2586	1.111
degree-pmfg	0.01823	0.3428	0.00464	0.3362	0.2342	0.5582
betweenness-pmfg	0.01741	0.4316	0.005136	0.4265	0.2952	0.8423
closeness-pmfg	0.01885	0.4374	0.006644	0.4345	0.2862	0.8879
pagerank-pmfg	0.01719	0.3502	0.003915	0.3489	0.2439	0.5474
eigenvector-pmfg	0.01542	0.3614	0.002604	0.3679	0.2649	0.5668
minvar	0.09126	0.1776	0.03185	0.1228	0.008528	0.5441

Figure 4.9: Table with stride = 500. We can notice the Min-var that here doesn't exhibit the minimum variance.

5. Conclusion

This study presents a detailed analysis of exchange rate data to construct a stabilized currency basket, leveraging data from Yahoo Finance spanning mid-2006 to December 2024. Through a combination of visualization, graph-based methods, and statistical metrics, we gained insights into currency behavior, volatility, and interrelationships. The raw exchange rate data revealed distinct trends and fluctuations influenced by major global events like the 2008 financial crisis and the COVID-19 pandemic, underscoring the need for stabilization.

Using Minimum Spanning Tree (MST) and Planar Maximally Filtered Graph (PMFG) representations, we captured meaningful currency relationships, with centrality metrics offering a deeper understanding of network structures. Adjustments to these metrics emphasized less central nodes, ensuring a more robust analysis. The study highlighted a trade-off between variance minimization and return optimization, with methods like Min-var excelling in stability, while centrality-based metrics provided opportunities to capitalize on currency fluctuations.

Here we can see all the metrics that try to stabilize the basket and how each individual currency goes.

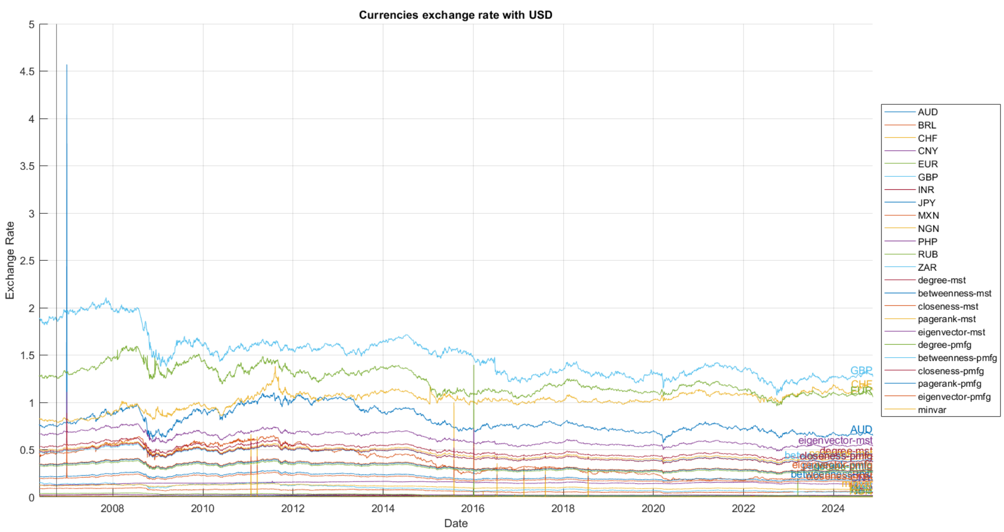


Figure 5.1: Despite some metrics are more suitable for this purpose and others help better on the standard returns, we can see that all the methods are way better than just normalize the currencies against a reference one (in our case, the US Dollar).

All methods demonstrated significant improvements over simple normalization against a reference currency, confirming the value of advanced analytical approaches. These findings have practical applications in finance, particularly for portfolio management and risk mitigation strategies.

Future research could extend this framework by incorporating additional currencies (for example including all BRICS+ economies), exploring alternative reference currencies, or examining the influence of external factors such as geopolitical events. This work offers a robust foundation for understanding and managing global exchange rate dynamics, enhancing strategies for both stability-focused and return-oriented objectives.

A. Weight smoothing

Our empirical experiments show that, if we recalculate the weights on a rolling window, the values of the weights change abruptly from one recalculation to the other. To mitigate the problem, while keeping the recalculation so that the weights remain up-to-date, we propose the simple approach of updating the weights through a rolling Exponential Moving Average (EMA). The EMA can be tuned by using a parameter α that selects the percentage of the old weights that are kept (Eq. A.1).

$$w'_t = \alpha \cdot w_t + (1 - \alpha) \cdot w_{t-1}; \tag{A.1}$$

In Figure A.1, it is possible to see the effect of the smoothing (same stride as in Figure 4.8).

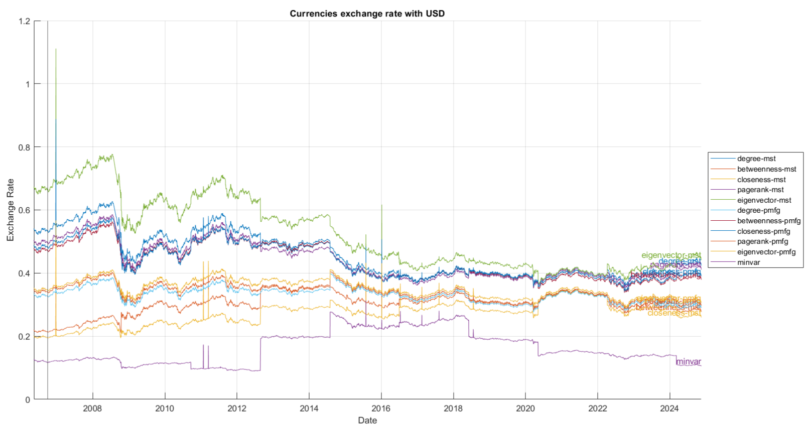


Figure A.1: Effect of exponential smoothing ($\alpha = 0.25$).

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