Foreign Portfolio Investment and Economic Dynamics: An Exploration of Emerging Economies

Abstract

In the intricate landscape of global finance, the interplay between emerging economies and their equity market integrations stands as a cornerstone of contemporary economic discourse. This research delves into the nuanced dynamics of equity market co-movements among 23 strategically selected countries, spanning the critical period from 2005 to 2019. Drawing upon daily closing prices of stock market indices from January 2013 to July 2020, we employ advanced network visualization techniques to craft a minimum-spanning tree network, elucidating the multifaceted interconnections within the global investment matrix.

At the heart of our analytical framework is the innovative metric of 'closeness,' offering a granular lens through which countries are categorized based on their unique roles and positions within the overarching portfolio investment network. Our exploration bifurcates into two primary avenues: Initially, we probe the intricate relationship between foreign portfolio investment and a spectrum of economic indicators, including assets, GDP, exchange rates, current accounts, and interest rates. These indicators are meticulously examined across three connectivity tiers—strong, moderate, and weak—providing a layered comprehension of their influence on investment dynamics. Subsequently, we adopt a clustering approach, segmenting countries based on these economic indicators, aiming to unveil the aggregated and collective economic trajectories that shape and are shaped by these clusters.

Our study's crux is to unravel the deep-seated symbiosis between foreign portfolio investments and the economic vitality of emerging markets. As these investments continually sculpt the global economic topography, understanding their foundational dynamics becomes paramount. This research not only augments the scholarly dialogue on the subject but also equips a diverse array of stakeholders, from policymakers to investors, with empirically grounded insights, pivotal for astute decision-making in an ever-evolving global financial milieu.

Key Words: clustering, investment network, economic indicators, closeness, minimum spanning tree.

Introduction

In the intricate tapestry of global finance, Foreign Portfolio Investment (FPI) has emerged as a cornerstone, playing a pivotal role in gauging a nation's appeal to the international investment community. Particularly within the realm of emerging economies, foreign investors have come to exert significant influence, often controlling a substantial portion of equity stock markets. The allure of these markets, however, extends beyond mere potential returns. It encompasses a complex matrix of determinants, ranging from financial robustness and favorable taxation policies to a conducive overall investment milieu (Ding & Sickles, 2019). The role of regional and economic alliances in shaping global investment patterns cannot be understated. Entities such as the European Union or ASEAN have been instrumental in amplifying investment flows, offering a semblance of predictability in an otherwise capricious global financial landscape. These affiliations, by fostering a stable framework, have often been the linchpin for investors seeking opportunities in emerging markets (Hakeem & Suzuki, 2017).

The dividends of FPI for recipient nations are manifold. Beyond the immediate infusion of capital, FPI acts as a catalyst, enhancing market efficiency and amplifying liquidity in capital markets. This liquidity surge facilitates easier access to funds for both corporations and households, often at more favorable borrowing rates, thereby catalyzing economic activities and fostering growth trajectories (Bekaert & Harvey, 1998).

The late 20th century, especially the transformative 1990s, witnessed emerging economies undergoing a metamorphosis. Forces of globalization, coupled with liberalization policies and the removal of trade impediments, ushered in an era of unprecedented international capital mobility. Equity investments, in particular, became the forefront of this financial revolution, reshaping the economic landscapes of these nations (Campbell & Hamao, 1989). This epoch of financial globalization, while bolstering domestic financial markets and fortifying local enterprises, also set the stage for stringent macroeconomic policy frameworks. Such frameworks were instrumental in enhancing financial resilience and stability across these emerging economies, ensuring they were better equipped to navigate the global financial maze (Ammer & Mei, 1996).

However, the path of financial integration was strewn with challenges. Seminal financial crises, especially the 1997 Asian financial debacle and the 2008 global financial crisis, underscored the vulnerabilities inherent in such integration. These events highlighted the intricate matrix of global financial interdependencies and their potential to trigger cascading repercussions across emerging markets (Huyghebaert & Wang, 2009). The dual nature of FPI is evident – while it serves as a harbinger of liquidity and growth, it is also susceptible to global shocks. Its volatility during global crises can amplify economic uncertainties, with abrupt reversals potentially destabilizing domestic capital markets and disrupting monetary equilibriums (Nanda, Mahanty, & Tiwari, 2010).

As the global financial architecture evolved, the role of FPI in shaping the economic trajectories of emerging markets became even more pronounced. The early 21st century saw a shift in the epicenter of global finance, with emerging economies becoming the focal points of international investment. This shift was not merely a consequence of the attractive returns these markets offered but was also a testament to their growing economic clout, policy reforms, and enhanced governance structures. Furthermore, technological advancements and digitalization played a pivotal role in democratizing access to financial information, thereby leveling the playing field. Investors, equipped with real-time data and sophisticated analytical tools, became more adept at identifying lucrative opportunities in these markets, further bolstering FPI flows. This confluence of factors underscored the symbiotic relationship between emerging economies and global investors, a relationship characterized by mutual growth and shared aspirations (Aghabozorgi & Teh, 2014).

Despite the challenges, a consensus within academic circles posits that the long-term advantages of portfolio investment overshadow its short-term volatilities. Our endeavor in this research is to delve deeper into this dynamic, exploring the nexus between economic indicators and portfolio investment. By doing so, we aim to provide empirical substantiation to this prevailing academic consensus, contributing to the broader discourse on FPI and its multifaceted implications for emerging economies (Chen Tong, 2018). Central to our investigative journey is the Coordinated Portfolio Investment Survey (CPIS) promulgated by the International Monetary Fund (IMF). This dataset offers a panoramic view of the cumulative investment a country garners, encapsulating contributions from a diverse spectrum of foreign investors, institutional agencies, and corporate entities (Lane and Milesi-Ferretti, 2010).

Our analytical framework is rooted in data spanning from 2005 to 2019, a period marked by significant global financial upheavals. These events, beyond their immediate financial implications, had profound socio-economic ramifications, reshaping the global financial landscape. As we navigate through this research, our objective remains to offer insights that are both academically rigorous and practically germane, contributing to the broader discourse on FPI in emerging economies.

Literature Review

The intricate relationship between an economy and its portfolio investment has long been a focal point of scholarly research. Over the years, the dynamics of this relationship have evolved, reflecting the changing contours of global finance and economic strategies. The nexus between economic performance and portfolio investment flows remains a central theme, with numerous studies delving into the multifaceted dynamics at play.

Rogoff (1999) was among the pioneers to investigate the transition from debt to equity financing. His work underscored a notable surge in equity investments across economies, suggesting a broader transformation in global financial strategies. This shift, particularly pronounced in emerging economies, was not merely an economic phenomenon. Bekaert & Harvey (1998) further built on this foundation, emphasizing the profound influence of private equity investment on these economies. Their subsequent research consistently highlighted the role of portfolio investments in fostering economic stability and driving growth in emerging markets. More recently, Gourinchas and Jeanne (2013) explored the global nature of capital flows, emphasizing the role of global banks and the implications for global financial stability.

Calvo, Leiderman, and Reinhart (1993) provided a comprehensive exploration of capital inflows to Latin America during the 1990s. Their insights illuminated both the opportunities and challenges presented by these flows, emphasizing the importance of understanding their determinants and macroeconomic implications. Eichengreen and Mody (1998) further enriched this discourse by examining the determinants of international bond spreads in emerging markets, shedding light on the interplay between global and country-specific factors. In a similar vein, explored the drivers of financial globalization, highlighting the role of policies and institutions in shaping global capital flows.

Chantapacdepong, P., & Shim, I. (2015) delved into the impact of bond inflow management measures on cross-market correlations in 12 Asia-Pacific economies over 2004–2013. Their findings indicate that the bond inflow management measures taken by a country tend to amplify the correlation of bond flows into that country with those into other regional countries. Actions to increase bond inflows significantly heighten bond flow correlations, while actions to decrease bond inflows don't show a significant impact. Over the long term, bond inflow management measures also elevate bond return correlations.

The Asian financial crisis served as a backdrop for Huyghebaert and Wang's (2009) study on equity market integration in East Asia. Utilizing advanced econometric tools, they highlighted the fragility and resilience of market integration, especially during tumultuous economic periods. Tiwari et al. (2013) complemented this by employing wavelet multiple correlations, offering a nuanced perspective on stock market integration and the potential benefits of long-term diversification. More recently, Koepke (2019) examined the drivers of capital flows in emerging markets, emphasizing the role of global financial conditions and country-specific factors.

Chen Tong's (2018) innovative approach visualized global stock market movements, offering a panoramic view of the interconnectedness of global financial markets. This was further complemented by the works of Lane and Milesi-Ferretti (2010) and Dabrowski (2010), who delved deeper into the intricacies of international financial market integration, challenging traditional econometric paradigms. Aviat and Coeurdacier (2007) explored the determinants of bilateral investment flows, emphasizing the role of information and transaction costs.

Rey (2015) provided a groundbreaking framework to decipher the global financial cycle, emphasizing the pivotal role of U.S. monetary policy in shaping capital flows and asset prices in emerging markets. This was particularly relevant in the aftermath of the 2008 financial crisis, a period that Bruno and Shin (2015) explored in depth. Their insights into the relationship between cross-border banking flows and global liquidity revealed the vulnerabilities of emerging markets to global banking conditions. Similarly, Obstfeld (2015) examined the global financial safety net, emphasizing the role of international reserves and swap lines in mitigating the risks associated with capital flow volatility.

Babu, M. S., Geethanjali, N., & Satyanarayana, B. (2012) explored clustering techniques for stock market prediction. They evaluated three clustering algorithms, K-Means, Hierarchical, and reverse K-means, and introduced the HRK method, combining Hierarchical agglomerative and Recursive K-means clustering. They aimed to predict short-term stock price movements post-financial report releases and found that the HRK method outperformed the Support Vector Machine (SVM) in prediction accuracy and profit generation.

Levine & Zervos (1996) and Agarwal (1997) delved into the nuances of investment flows, with a particular focus on market liquidity and the magnetic pull of a nation's economic health on investments. Forbes & Rigobon (2002) and Claessens & Forbes (2001) further enriched this discourse, exploring the complexities of stock market co-movements and international financial contagion, respectively. In a more recent study, Ahmed and Zlate (2014) explored the drivers of emerging market capital flows, emphasizing the role of global push factors. Their findings underscored the significance of understanding the interplay between global and domestic factors in influencing these flows.

In sum, the vast tapestry of literature on foreign portfolio investment and economic markers paints a complex yet enlightening picture. Our research seeks to integrate these diverse studies, aiming to provide a comprehensive understanding of the symbiotic relationship between foreign portfolio investment and economic markers, with a keen focus on emerging economies.

Objectives of the study:

The primary aim of this research is to elucidate the intricate relationship between foreign portfolio investment and the economic dynamics of emerging economies. Drawing from an extensive review of existing literature and empirical analyses, the objectives are manifold:

1. To dissect the historical and contemporary trends of foreign portfolio investment in emerging markets and assess their implications on macroeconomic behaviors.
2. To critically evaluate the impact of economic health on attracting portfolio investments, emphasizing the role of policy frameworks and market conditions.
3. To analyze regional variations in investment patterns and the subsequent economic outcomes, shedding light on unique challenges and opportunities specific to certain geographies.
4. To comprehend the aftermath of global financial crises on the flow and influence of foreign portfolio investments in emerging economies.

Through these objectives, the study endeavors to offer valuable insights for policymakers, investors, and academicians, aiming to shape future strategies and research directions in the domain of global finance and economic development.

Data Sources:

Our exploration into portfolio investment networks heavily relies on the Coordinated Portfolio Investment Survey (CPIS) disseminated by the International Monetary Fund (IMF). The CPIS dataset encapsulates the cumulative investment that a country attracts, encompassing contributions from foreign investors, agencies, and corporations.

We anchored our analysis to data spanning from 2005 to 2019. This 15-year window is pivotal, witnessing watershed moments in global finance such as the 2008 Global Financial Crisis, the European Debt Crisis, and the tumultuous journey of Brexit. Each of these events, aside from its direct financial ramifications, also rippled through societies. For instance, many households across affected nations grappled with escalated taxation and a surge in unemployment, stymieing economic progression.

Our dataset casts a wide net of 23 emerging economies. These countries, earmarked as nodes in our network, have been cherry-picked owing to their significance in terms of economic output and pertinent market statistics.

Methodology

Constructing the Network:

The foundation of our analysis is the Minimum Spanning Tree Network (MSTN) approach. In this method, nodes represent countries, and they are interconnected based on the smallest possible edge weights in an undirected weighted graph. This approach is particularly useful for visualizing and understanding the complex relationships in large datasets.

Starting with the correlation matrix, Corr(I), derived from the CPIS investment data of 23 countries, we assessed the co-movements between portfolio investments. Given the 253 potential edges in the graph, direct interpretation can be overwhelming. The MSTN method simplifies this by preserving only the most significant links while ensuring the network remains connected.

$$D(I) = \sqrt{2*(1 - Corr(I)}$$

$$0 \leq D(I) \leq 2$$

The Corr(I) matrix can encompass both positive and negative values. To address potential issues associated with negative values, we transformed the matrix into corresponding Grower distances. These distances, inversely proportional to correlation values, provide a clearer representation of the closeness of countries in terms of economic integration. For the construction of the MSTN, Kruskal's Algorithm was employed. This algorithm is renowned for its ability to select links judiciously, ensuring the resultant graph is cycle-free and connected.

Centrality Measures:

Degree Centrality: This is a primary measure that quantifies the number of edges linked to a node. It's instrumental in identifying the most connected nodes in the network. The distinction between incoming (in-degree) and outgoing edges (out-degree) provides insights into the directionality of these connections.

$$DC(v) = \frac{number\ of\ links\ connected\ to\ node\ v}{total\ number\ of\ nodes - 1}$$

Closeness Centrality: This measure reflects the average distance from one node to all other nodes in the network. It's pivotal in understanding the financial information richness and liquidity access of a particular node.

$$CC(v) = \frac{n - 1}{\sum_{u \neq v} d(v, u)}$$

Where n is the total number of nodes and $d(v, u)$ is the shortest distance between nodes v and u.

Clustering Coefficient: This coefficient provides insights into the local cohesion or clustering of the network. It denotes the likelihood that the neighbors of a node are also neighbors of each other.

$$C(v) = \frac{2T(v)}{deg(v)(deg(v) - 1)}$$

Where $T(v)$ is the number of triangles through the node v and $deg(v)$ is the degree of v.

Criteria for Node Selection: Nodes, in our context, represent countries. Based on the Closeness Centrality (CC), we classified countries into three connectivity levels. This stratification aids in understanding the varying degrees of integration and connectivity among the countries.:

- Level 1: Strong Connectivity (e.g., Egypt)
- Level 2: Intermediate Connectivity (e.g., Mexico)
- Level 3: Weak Connectivity (e.g., Russia)

Clustering: Hierarchical clustering, with an emphasis on the agglomerative approach, was employed. This bottom-up strategy begins by treating each object as a single cluster, and then successively merging or "agglomerating" pairs of clusters until all clusters have been merged into a single cluster that contains all objects. Ward's linkage technique, which we adopted, is distinct in its focus on minimizing the variance within each cluster. The metric foundational to Ward's method is the squared Euclidean distance, which emphasizes the minimized fluctuation within clusters.

$$d_{ij} = d(\{X_i\}, \{X_j\}) = \|X_i - X_j\|^2$$

Correlation between Economic and Network Indicators:
Data pertaining to economic indicators, spanning from 2005 to 2019, was meticulously sourced from the IMF's International Financial Statistics (IFS). This dataset encompasses a range of indicators, including Assets, GDP, Exchange rate, Interest rate, and the Current account as a percentage of GDP. To ascertain the correlation between these economic indicators and the network measures, we employed the VAR (vector autoregressive) model. The VAR model, in this context, allows us to understand the dynamic interplay between the economic indicators and their influence on portfolio investments.

Empirical Results:

The analysis of the MSTN provided a differentiated approach to connectivity among emerging economies, which, when integrated with the GN, gave a clear geographical as well as relational representation of connections. The nodes were distinctly separated into three levels:

1. Level 1 (Strongly Connected): Comprising 8 nodes, countries in this category exhibited a unique pattern in their foreign portfolio investment (FPI) relationships. Notably, countries with higher assets typically witnessed higher FPIs, albeit the dependency of FPI on assets was least pronounced in this group. Interestingly, while FPI increased with GDP for these countries, the relationship between FPI and the Current account was inversely related. On the interest rate front, a negative correlation with FPI was observed.
2. Level 2 (Moderately Connected): Countries in this bracket displayed a reverse relationship between GDP and FPI when compared to Level 1 countries. The exchange rate mirrored the GDP trend. Moreover, FPI showcased a direct relationship with both the current account and the interest rate, signifying that a higher current account and interest rate would mean higher FPI.

3. Level 3 (Weakly Connected): This group shared characteristics with both Level 1 and Level 2 nations. Like Level 2, the trend for GDP and the exchange rate was reversed when compared to FPI. The relationship between the current account and FPI was positive, similar to Level 2. However, like Level 1 countries, there was a negative correlation between interest rates and FPI.

Figure - 1: MSTN Network for the emerging economies.

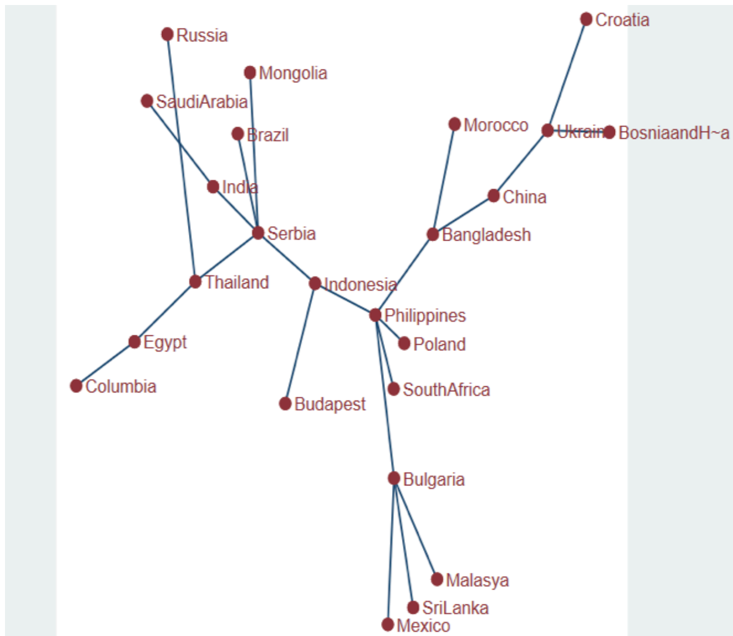


Figure - 1 showcases the MSTN Network representation for the emerging economies, providing a visual aid to the connectivity classifications discussed.

The intricate patterns and correlations observed among the different levels emphasize that a country's connectivity level significantly impacts the relationship between its economic indicators and FPI. Enhancements in connectivity patterns can refine these relationships, offering emerging economies strategies to better align their economic policies with FPI.

Clustering results:

Table - 1: The Indicators for countries and the Cluster ID generated after clustering for 2016

Countries	% delta return	GDP	IR	EXR	BoP	Volatility	Cluster ID
Bangladesh	0.03	221415000000	3.45	78.47	-10505302542	1741.89	1

Bosnia and Herzegovina	-0.17	16913330694	3.77	1.77	-2810928851	590.1	2
Bulgaria	0.28	53785050339	3.76	1.77	2710620000	475.25	2
China	-0.06	11233300000000	2.9	6.64	255737000000	2998.99	4
Croatia	0.2	51596973259	6.93	6.81	671239690	1770.08	2
India	0.02	2294800000000	6.23	67.2	-41579206265	26380.08	3
Indonesia	0.17	931877000000	9.22	13308.33	8234324960	5024.99	3
Mongolia	-0.02	11186734674	17.13	2140.29	-497136	11577.3	2
Philippines	0	318627000000	4.31	47.49	-28505668861	7289.74	1
Poland	0.06	472037000000	1.5	3.94	18721000000	1310.3	1
Russia	0.53	1276790000000	9.48	67.06	66256050000	664.03	3
Serbia	0.1	40630392019	4.5	111.28	-2447273760	152.03	2
SriLanka	-0.04	82401038710	5.39	145.58	-5993868515	603.98	2
Thailand	0.22	413430000000	1.76	35.3	56051035538	1432.18	1
Hungary	0.1	127507000000	1.11	281.52	11180768729	27112.33	2
Columbia	0.35	282825000000	9.03	3054.12	-12705450738	1304.81	1
Brazil	0.2	1795700000000	40.7	3.49	14188038177	21999.79	3
Egypt	0.41	332928000000	6.92	10.03	-34677100000	8018.51	1
Morocco	0.74	103312000000	3.12	9.81	-10739249607	9844.89	2
Mexico	0.31	1077900000000	-0.63	18.66	-22029591091	5166.48	3
Saudi Arabia	-0.09	644936000000	2	3.75	2749855279	6327.86	1
Malaysia	0.04	301255000000	2.83	4.15	19990335309	581.08	1
South Africa	0	296357000000	3.03	14.71	1640308414	1308.18	1

Table - 2: The Indicators for countries and the Cluster ID generated after clustering for 2019

Countries	% delta return	GDP	IR	EXR	BoP	Volatility	Cluster ID
Bangladesh	-0.21	302571000000	4.88	84.45	-19561753265	144.83	1
Bosnia and Herzegovina	0.09	20047848435	1.17	1.75	-2974251516	47.78	2
Bulgaria	-0.03	67927179737	-0.1	1.75	2318360000	11.37	2
China	0.24	14342900000000	2.73	6.91	164122000000	160.96	4
Croatia	0.17	60415553039	3.96	6.62	-317390285	85.92	2
India	0.14	2875140000000	6.99	70.42	-73451671323	1607.64	3
Indonesia	0.02	1119190000000	8.62	14147.67	-4232066107	148.86	3

Mongolia	-0.09	13852850259	8.01	2663.54	-833604449	569.11	2
Philippines	0.04	376796000000	6.28	51.8	-36423258165	143.75	1
Poland	-0.06	592164000000	1.5	3.84	30865000000	77.4	1
Russia	0.42	1699880000000	4.79	64.74	129038000000	79.14	3
Serbia	0.08	51409167351	2.75	105.25	-5109391875	6.02	2
SriLanka	0	84008783756	8.86	178.74	-5147667482	25.17	2
Thailand	0.01	543650000000	3.31	31.05	49964813817	43.96	1
Budapest	0.16	160967000000	-2.61	290.66	5144893843	1588.47	2
Columbia	0.25	323803000000	7.18	3280.83	-12353444442	68.94	1
Brazil	0.29	1839760000000	31.99	3.94	5406792771	2651.4	3
Egypt	0.06	303175000000	2.19	16.77	-25428193000	550.45	1
Morocco	0.08	118725000000	2.25	9.62	-10817897570	288.95	2
Mexico	0.08	1258290000000	4.98	19.26	-3058761680	186.23	3
Saudi Arabia	0.08	792967000000	2.5	3.75	75818975315	441.73	1
Malaysia	-0.05	364702000000	4.79	4.14		17.05	
SouthAfrica	0.07	351432000000	5.87	14.45	1728448788	43.05	1

From the data presented in Tables 1 and 2, it's evident that, over the short run, countries tend to stay within their specific clusters, underscoring the stability of fundamental economic dynamics. This clustering offers a hierarchical and nuanced lens to view global economic trajectories, revealing more than just surface-level insights. For instance, China’s unique placement in Cluster 4 underscores its unparalleled economic trajectory. Its vast economic magnitude, coupled with a consistent growth pattern, distinguishes it from its peers. Meanwhile, countries in Cluster 3, such as India, Brazil, and Indonesia, emerge as key players, indicating their potential to challenge established economies in the future. These countries are becoming increasingly pivotal in the global scene, as can be seen by sectors like India's IT and service industries or Brazil's expansive agro-industry.

Moreover, the breadth of economic indicators, from GDP to volatility, used for clustering shows that economies are multifaceted, and influenced by a myriad of factors. These clusters can have profound real-world implications. For instance, investors might tailor their strategies based on the growth patterns identified within these clusters, especially focusing on emerging powerhouses in Cluster 3. Governments, on the other hand, can utilize this data for policy formulation and benchmarking. Countries in Cluster 2 might analyze the growth drivers of Cluster 3 nations to emulate successful strategies. Furthermore, countries within the same cluster could find synergies in trade and diplomacy, given their shared economic profiles.

In essence, the clustering approach paints a detailed portrait of global economies, showcasing their growth, interactions, and challenges in the 21st century. By grouping nations based on comprehensive economic indicators, we simplify the complex web of global financial dynamics, offering valuable insights to policymakers, investors, and businesses alike.

Table - 3: The Cluster sizes based on the similarities between the economies for 2016

2016	Frequency	Percent	Cumulative
1	9	39.13	39.13
2	8	34.78	73.91
3	5	21.74	95.65
4	1	4.35	100
Total	23	100	

Table - 4: The Cluster sizes based on the similarities between the economies for 2019

2019	Frequency	Percent	Cumulative
1	8	36.36	36.36
2	8	36.36	72.73
3	5	22.73	95.45
4	1	4.55	100
Total	22	100	

Tables 3 and 4 provide a detailed understanding of how nations cluster based on shared economic characteristics for 2016 and 2019. Observations from both years underscore intriguing patterns of consistency in the economic trajectories of these nations.

The marginal change in the first cluster, from nine nations in 2016 to eight in 2019, suggests a dynamic shift within emerging economies. For example, the rapid rise of the Bangladeshi textile industry on the global stage might indicate that its economic profile is evolving, potentially moving towards another cluster in the near future. Conversely, the second cluster's stability over the years might be exemplified by countries like Bulgaria, which has experienced steady growth propelled by its tourism and IT sectors.

China's unique position in the fourth cluster underscores its distinct economic model—a "socialist market economy." This blend of market forces with state interventions has fostered unparalleled growth rates, distinctly setting China apart from its global counterparts.

The unwavering nature of these clusters over a three-year span underscores the principle of path dependency in economic theory. Essentially, the choices an economy makes today are heavily influenced by its historical decisions. For instance, India's focus on its IT and services sector over the years has firmly rooted it in its respective cluster, much like Russia's economic reliance on its abundant natural resources.

This consistent clustering suggests a strategy for economists and policymakers. By concentrating on representative nations from each cluster, they can glean insights into the broader economic group without sifting through the intricacies of each individual country. This is akin to market analysts examining 'bellwether' stocks as indicators for an entire sector's performance. Such a methodical approach offers a way to streamline analysis without compromising the depth of understanding.

Table - 5: The Cluster means for parameters of different economies for 2016

2016	Delta Return	GDP	IR	EXR	BOP	Volatility
1	0.1139932	3.65E+11	3.87037	361.3283	1.42E+09	3257.172
2	0.1495374	6.09E+10	5.71428	337.3529	-9.29E+08	6515.745
3	0.2448498	1.48E+12	13.00281	2692.947	5.01E+09	11847.07
4	-0.05844	1.12E+13	2.901775	6.644478	2.56E+11	2998.986
Total	0.1473064	9.72E+11	6.454931	844.4416	1.25E+10	6246.733

Table - 6: The Cluster means for parameters of different economies for 2019

2019	Delta Return	GDP	IR	EXR	BOP	Volatility
1	0.0296414	4.48E+11	4.213765	435.8671	8.08E+09	189.2649
2	0.0560401	7.22E+10	3.036735	407.2412	-2.22E+09	327.8491
3	0.1886156	1.76E+12	11.4745	2861.208	1.07E+10	934.6537

4	0.237226	1.43E+13	2.725124	6.908385	1.64E+11	160.9611
Total	0.0848071	1.24E+12	5.368256	957.1733	1.20E+10	407.7792

Tables 5 and 6 present an insightful breakdown of various economic indicators across different country clusters for the years 2016 and 2019. These insights allow for a deeper understanding of the performance and dynamics of economies in the global context, and there are significant observations to be drawn from this data.

The shift in the mean change of returns from 2016 to 2019 suggests that there has been a remarkable transformation in the economic performance of the countries within these clusters. For instance, Cluster 4, presumably led by China as its major contributor, witnessed a pivot from negative to positive returns. This mirrors China's evolving role on the global stage, moving from a manufacturing-led growth strategy to one driven by domestic consumption and technological innovation.

Conversely, the GDP values across clusters remain comparatively stable, underscoring the general resilience and consistency of these countries' economies. The overarching trend across both years, with Cluster 4 leading the pack, is a testament to the burgeoning might of the Asian economies, especially China, in comparison to their global counterparts. The trajectory of the mean GDP value aligns with what we know about the real world; China has consistently been the second-largest global economy after the US, with countries from Cluster 3, like India, increasingly asserting their economic influence.

One intriguing avenue of exploration is the notion of substituting clusters with representative nations when it comes to macroeconomic analyses. This methodology mirrors the concept of "benchmark countries" in global economics. For instance, using the United States as a benchmark for Western economies or China for East Asian economies offers a simplified yet insightful understanding of larger trends.

Furthermore, the consistent risk values across the clusters resonate with established economic theories. As Baz et al. (1999) posited, country risks, especially when considering investments, tend to remain relatively stable over short periods. It's pivotal for investors to recognize that, with Cluster 3 being the most volatile, diversifying investments across clusters may be a prudent strategy to mitigate country-specific risks.

These tables shed light on both the static and dynamic facets of global economies. By analyzing such clusters, policymakers, and investors can craft strategies that are both informed and adaptive to the shifting sands of the global economic landscape.

In our empirical exploration, we've chosen to delve deeper into three distinct emerging economies: Russia, Egypt, and Mexico. The rationale behind this selection is multifaceted. Firstly, these nations represent diverse geographical and economic landscapes, spanning Eastern Europe, North Africa, and North America. This diversity ensures our findings encapsulate varied economic cultures and responses. Secondly, each of these countries has been at the epicenter of significant economic events in recent years. Russia's intricate dance with global economic sanctions, Egypt's journey through political and economic reforms, and Mexico's evolving trade dynamics, especially with its northern neighbor, the U.S., offer rich contexts for our analysis. Furthermore, the robustness and comprehensiveness of data available for these nations bolster the reliability of our findings. By focusing on these countries, we aim to shed light on broader patterns and trends that might resonate with other emerging markets, while also addressing unique country-specific dynamics.

Based on Tables 7, 8, and 9, The Vector Autoregression (VAR) results for Russia, Egypt, and Mexico provide a nuanced understanding of the determinants of investment in these emerging economies. In Russia, the lagged investment values do not seem to play a significant role in determining current investment levels. This could be indicative of a more dynamic investment environment where past trends do not necessarily dictate future investment flows. The significant positive relationship between assets and investment underscores the importance of a robust asset base in attracting investments. This aligns with the theory that a strong asset base can serve as collateral, reducing risks for foreign investors. Conversely, the negative relationship between GDP and investment in Russia might be reflective of certain macroeconomic challenges or perhaps policy decisions that have deterred foreign investments. The negative influence of the exchange rate and interest rate on investment suggests that currency stability and monetary policy play crucial roles in shaping investment decisions.

Egypt presents a contrasting picture. While assets remain a significant determinant, as seen in Russia, other macroeconomic variables like GDP, exchange rate, and interest rate don't significantly influence investment. This might hint at Egypt's unique economic landscape, where perhaps political or regional factors play a more dominant role than pure economic indicators.

Mexico's results are particularly intriguing. The significant positive influence of the first lagged investment value suggests a momentum effect, where past positive investment flows can lead to increased current investments. This might be indicative of investor confidence, where a positive investment trend can attract further investments. The strong influence of assets, similar to both Russia and Egypt, reaffirms the universal importance of a robust asset base in attracting foreign investments. The negative relationship between GDP and investment, coupled with the negative influence of the exchange rate, might be reflective of Mexico's economic challenges during the period under study. However, the positive influence of the current account to GDP ratio and interest rate suggests that trade balances and monetary policy can act as counterbalancing forces.

In the context of our study, these empirical results highlight the multifaceted nature of investment determinants in emerging economies. While some determinants like assets consistently play a significant role across countries, others like GDP, exchange rate, and interest rate vary in their influence. This underscores the importance of a country-specific approach when formulating policies to attract foreign investments. The results also resonate with the broader economic theory that investments are influenced by a combination of macroeconomic indicators, policy decisions, and country-specific factors.

Figure - 2: Dendrogram Plot for the top 10 branches after clustering for the year 2016

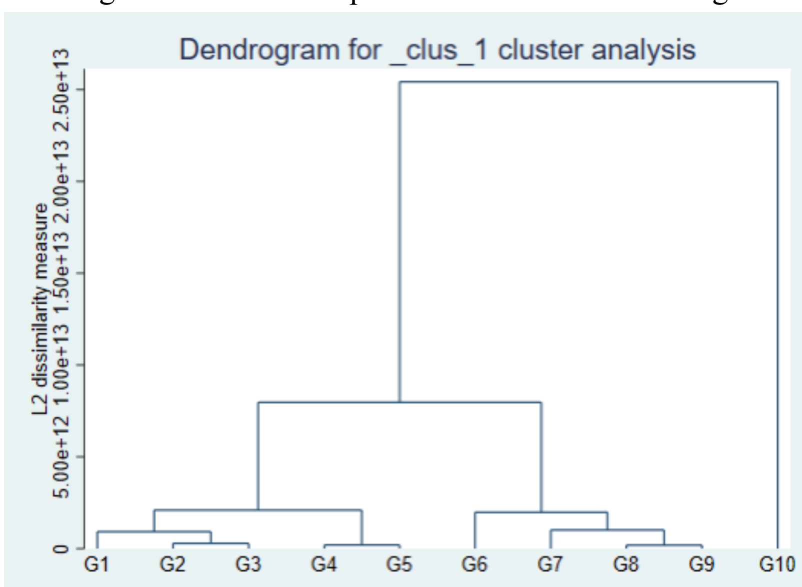
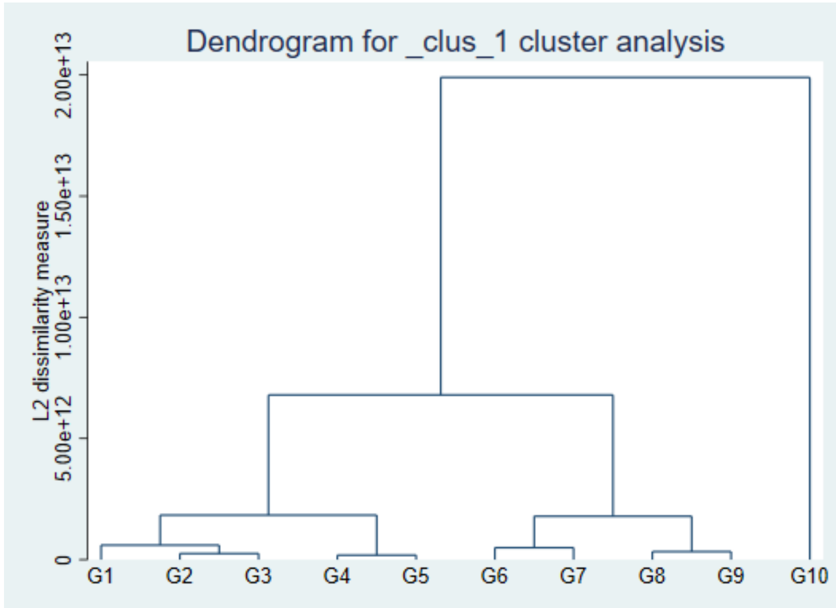


Figure - 3: Dendrogram Plot for the top 10 branches after clustering for year 2019



The dendrogram analysis in Figures 2 and 3 offers a hierarchical visualization of the relationships between different country clusters for the years 2016 and 2019. By interpreting these dendrograms from the base to the peak, we are essentially unfolding a story of how global economies have evolved and changed in terms of their similarity and interconnectedness.

The rapid merging of clusters G1 to G5 in both years implies that there might be inherent, long-standing commonalities between these economies. This could relate to regional interdependencies, shared growth strategies, or even mutual economic challenges. For instance, countries in the European Union or the ASEAN bloc might display similar economic behaviors due to their integrated trade policies and shared regional objectives.

On the contrary, the variances in the merging patterns of clusters G6 to G9 between the two years showcase subtle shifts in economic landscapes. In 2016, the order of merging suggests that G6 and G7's economies might have been more independent or distinct compared to 2019 when they merged earlier. Such shifts could be driven by various factors, including political changes, trade policies, or global events. For instance, the Brexit vote in 2016 and subsequent negotiations might have influenced the UK's economic parameters, causing shifts in its clustering relative to European neighbors.

The constancy in the ultimate clustering outcome across both years hints at the overall stability of global economies. This is analogous to the notion that while countries might evolve and grow, foundational elements of their economies—like the primary sectors of production or export partners—may remain relatively constant over short periods.

While our conclusions provide a nuanced perspective on global economic relationships, they're primarily based on two data points (2016 and 2019). To achieve a more holistic view, it might be beneficial to analyze dendrograms across more years, which would capture longer-term trends and shifts. This could highlight, for example, the gradual rise of emerging economies or the relative decline of previously dominant ones.

In summing up, the twin methods of analysis underscore the symbiotic relationship between financial and economic factors in determining the similarity of economies. It is evident that while financial markets react to immediate events and stimuli, they also encapsulate broader economic narratives and indicators. The choice between clustering based on pure financial returns or a more holistic set of economic indicators hinges on the specific objectives of the analysis. However, the alignment in outcomes from both methods emphasizes that the health of financial markets is invariably intertwined with the broader economic health of a nation.

Conclusion:

The global investment network, with its intricate interconnections, can be aptly likened to a spider's web. Within this vast web, each node symbolizes a distinct economy, and the threads weaving them together represent their multifaceted financial and economic interdependencies. The centrality of these nodes, which extends beyond mere direct connections, encapsulates the strength, influence, and significance of these connections within the network.

Drawing inspiration from an exhaustive literature review, we embarked on a journey to understand the myriad determinants of FPI. Our empirical foray into the economic terrains of Russia, Egypt, and Mexico further illuminated this understanding, emphasizing the pivotal role of country-specific nuances. While assets consistently emerged as a universal determinant of FPI, the influence of other variables, such as GDP, exchange rate, and interest rate, varied, underscoring the imperative for bespoke policy interventions.

Our analysis revealed the profound significance of clusters formed based on centrality measures. Level 1 nodes, emblematic of powerhouse economies or global financial hubs, wield considerable influence on the economic dynamics of their interconnected counterparts.

Conversely, Level 3 nodes, though weaker in connectivity, offer unique diversification benefits, potentially insulating them from global financial upheavals. The K-means clustering approach employed in our study elucidated these intricate relationships, offering a panoramic view of the global investment milieu.

Furthermore, our research reaffirms a foundational principle of investment: diversification. While strongly connected economies, such as Level 1 nodes, present lucrative investment avenues, they also harbor correlated risks. A judicious blend of investments across nodes of varying connectivity levels can strike a harmonious balance between potential returns and associated risks.

At its essence, our study accentuates the deep-seated symbiosis between financial markets and overarching economic narratives. While financial markets are inherently reactive, their pulse is intrinsically linked to broader economic stories. This intricate dance between markets and economies presents a spectrum of challenges and opportunities for a diverse array of stakeholders, from policymakers to investors.

As we stand at the cusp of an evolving global economic landscape, the insights distilled from our research can serve as a beacon, illuminating the path for stakeholders navigating the complex realm of foreign portfolio investments in emerging markets. The road ahead, though fraught with uncertainties, is also rife with untapped potential and opportunities. In summation, in the intricate ballet of finance and economics, it's not just about forging connections but ensuring these bonds are resilient and symbiotic. In this intricate dance, as our findings suggest, connectivity reigns supreme.

Future Research:

The findings of this study open avenues for several promising directions in future research. Expanding the temporal scope of analysis to include longer timeframes and capturing the impact of various market cycles and economic events could provide a more comprehensive understanding of the evolving relationship between foreign portfolio investment and economic indicators. Exploring the influence of cultural, social, and institutional factors on investment decisions, in addition to economic variables, could add a layer of depth to the analysis. Incorporating machine learning and artificial intelligence techniques to predict portfolio investment flows based on historical data and external factors might offer predictive insights for investors and policymakers. Furthermore, investigating the impact of sustainable investing practices, environmental, social, and governance (ESG) factors on portfolio investment patterns could shed light on the emerging trends in responsible investing. Lastly, a cross-sectional analysis of various clusters and their performance during times of market stress or geopolitical shifts could yield valuable insights into the resilience of different economies. By pursuing these avenues, researchers can contribute to a more holistic and dynamic understanding of the intricate relationship between portfolio investment and emerging economies, ultimately guiding stakeholders toward more informed decisions.

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Appendix

Table - 7: VAR Results for Russia

Russia	Coef.	Std. Err.	z	P>z
investment				
L1.	0.1788503	0.2188606	0.82	0.414
L2.	0.0823968	0.1846846	0.45	0.655
Assets	0.5684922	0.1115807	5.09	0
GDP	-5.00E+09	1.94E+09	-2.57	0.01
Exchange Rate	-1.63E+13	7.10E+12	-2.3	0.021
Current A/c GDP	0.1076379	0.3645258	0.3	0.768
Interest Rate	-2.52E+10	9.97E+09	-2.52	0.012
_cons	6.57E+11	3.02E+11	2.18	0.03

Table - 8: VAR Results for Egypt

Egypt	Coeff	Std Err	z	P>z
investment				
L1.	0.288575	0.2440632	1.18	0.237
L2.	-0.002811	0.2978745	-0.01	0.992
Assets	0.2761626	0.1125029	2.45	0.014
GDP	3.09E+07	7.68E+07	0.4	0.688

Exchange Rate	1.14E+11	9.93E+10	1.15	0.251
Current A/c GDP	-0.5503985	0.4514952	-1.22	0.223
Interest Rate	-5.92E+08	1.57E+09	-0.38	0.707
_cons	-4.20E+10	2.93E+10	-1.43	0.152

Table - 9: VAR Results for Mexico

Mexico	Coeff	Std Error	z	P>z
investment				
L1.	0.328626	0.1721813	1.91	0.056
L2.	-0.1259673	0.1129593	-1.12	0.265
Assets	1.172402	0.171347	6.84	0
GDP	-5.65E+09	1.31E+09	-4.31	0
Exchange Rate	-3.76E+12	1.06E+12	-3.54	0
Current A/c GDP	2.240378	0.7597503	2.95	0.003
Interest Rate	1.54E+10	5.07E+09	3.03	0.002
_cons	5.56E+11	1.78E+11	3.12	0.002