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Exploring the Interplay between Audit Standards and Investment Patterns: A Cluster-Based Analysis of FDI and FPI Across Nations

Ioana Vinasi

Department of Cybernetics and Statistics, Faculty of Economics and Business Administration

Babeș-Bolyai University

Email: ioana.ianos@econ.ubbcluj.ro

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Abstract

This study examines the impact of Strength of Audit and Reporting Standards (SARS) on Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI) across 84 countries (2007–2017). SARS enhances transparency, reduces information asymmetry, and fosters investment efficiency, boosting investor confidence. Using Compound Annual Growth Rate (CAGR), clustering methods, and regression analysis, the study evaluates how governance quality shapes investment flows. The findings reveal SARS significantly influences portfolio investments, attracting higher FPI through better governance, while its effect on FDI is weaker due to FDI's reliance on long-term factors like market size and resources. Clustering analysis highlights that developed economies with robust SARS consistently attract investments, whereas resource-dependent nations with weaker governance face challenges despite their natural wealth. Strengthening SARS through international standards, enforcement, and region-specific reforms is crucial for attracting foreign investments and fostering economic resilience. For investors, SARS is a reliable indicator of market stability, particularly for guiding portfolio investments. SARS plays a pivotal role in shaping global investment patterns, especially FPI, making its improvement essential for sustainable growth and investor confidence.

Keywords*:* Strength of Audit and Reporting Standards (SARS), Foreign Direct Investment (FDI), Foreign Portfolio Investment (FPI), Compound Annual Growth Rate (CAGR), Clustering methods, Regression analysis

Introduction

The globalized economy increasingly depends on the free flow of capital across borders, making Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI) critical to fostering growth and economic integration. Governance mechanisms like the Strength of Audit and Reporting Standards (SARS) are pivotal in shaping these capital flows. SARS serves as the backbone of financial transparency, addressing issues such as information asymmetry, moral hazard, and adverse selection—factors that can inhibit investment. Despite its centrality, the role of SARS in driving investment dynamics remains underexplored, highlighting the importance of studying its impact on FDI and FPI.

The interplay between SARS and investment patterns deserves attention for several reasons. First, while significant progress has been made in understanding FDI and FPI drivers, the nuanced effects of governance quality, particularly SARS, remain insufficiently examined. FDI, with its reliance on long-term factors like market size and resources, contrasts sharply with FPI, which responds swiftly to improvements in governance and transparency. This divergence necessitates a targeted exploration of SARS as a determinant of diverse investment types. Furthermore, developing countries face significant governance challenges that deter foreign investments. For these nations, improving SARS could serve as a powerful lever to attract capital, build investor confidence, and support sustainable economic growth. This study is significant because it bridges gaps in understanding the distinct ways in which SARS affects FDI and FPI. For policymakers, it provides a robust framework for reforming financial reporting practices to attract investments. For investors, it offers insights into how SARS influences risk, volatility, and returns, enabling better decision-making. Additionally, the research holds relevance for international institutions seeking to promote governance reforms that align with global standards. By identifying region-specific governance challenges, the study supports tailored policy interventions that can enhance investment efficiency and economic stability.

This study benefits various stakeholders by providing critical insights into the relationship between the Strength of Audit and Reporting Standards (SARS) and foreign investments. Policymakers, for instance, can use the findings to design effective strategies to strengthen financial governance, thereby attracting both Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI) while fostering economic development. Investors, particularly those focused on portfolio investments, can leverage this analysis to better understand how SARS impacts risk, volatility, and returns, enabling them to make informed decisions in diverse markets.

For developing nations, where governance structures often lag, this research offers a clear pathway to improve their competitiveness in global financial markets through targeted SARS reforms. Such improvements can attract much-needed capital, support industrialization, and stimulate economic growth. Additionally, international institutions advocating for economic development can utilize the insights to encourage the adoption of standardized financial reporting and transparency frameworks, aligning national policies with global best practices. Academics and researchers also benefit from the study, as it fills a crucial gap in the literature by exploring the differential effects of SARS on FDI and FPI. This understanding forms a foundation for further scholarly work and offers new perspectives on the governance-investment nexus. In essence, this research serves as a valuable resource for all stakeholders seeking to enhance investment flows and foster sustainable economic growth through improved financial governance.

Strengthened SARS is not just a regulatory tool but a driver of economic transformation. By enhancing transparency and reducing risks, SARS fosters sustainable investment patterns and builds economic resilience. This is particularly effective in attracting FPI, which is highly sensitive to governance quality. Moreover, SARS reforms align national systems with international standards, offering competitive advantages in an increasingly interconnected global economy. This study reinforces the argument that improving SARS is vital for fostering investor confidence and achieving equitable and sustainable growth.

In the contemporary globalized economy, Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI) serve as pivotal channels for capital flow, significantly influencing economic growth and development across countries (Daude & Stein, 2007). The efficiency and attractiveness of these investment flows are profoundly affected by the quality of financial reporting and audit standards within a nation (Biddle, Hilary, & Verdi, 2009). High-quality audit and reporting standards (SARS) enhance transparency, reduce information asymmetry, and mitigate risks associated with moral hazard and adverse selection, thereby fostering a conducive environment for both FDI and FPI (Costello & Wittenberg-Moerman, 2011).

Financial reporting quality (FRQ) is instrumental in aligning actual investment levels with optimal investment needs, as it provides reliable information that investors use to make informed decisions (Biddle et al., 2009). Improved FRQ leads to greater investment efficiency by reducing frictions in capital markets (Cheng, Dhaliwal, & Zhang, 2013). For instance, Biddle and Hilary (2006) found that timely and accurate financial reporting correlates with higher capital investment efficiency, suggesting that countries with robust SARS are more likely to attract and efficiently utilize foreign investments.

The strength of SARS is not only crucial for domestic investors but also significantly impacts foreign investors' decisions (Daude & Stein, 2007). High-quality reporting standards increase a country's credibility, making it a more attractive destination for foreign capital (Barth, Cahan, Chen, & Venter, 2017). Barth et al. (2017) demonstrated that integrated report quality positively influences capital market outcomes and real investment effects, emphasizing the economic consequences of superior financial reporting.

The strength of audit and reporting standards is a critical factor influencing investment efficiency and the attractiveness of countries to foreign investors. Clustering methods such as k-means and hierarchical clustering provide valuable insights into the relationships between SARS, FDI, and FPI by allowing researchers to identify patterns and groupings that inform policy and investment strategies (Romesburg, 2004). This article aims to explore these relationships further, utilizing clustering techniques to analyze how variations in SARS impact investment flows across different countries.

In analysing the complex relationships between FDI, FPI, and SARS across different countries, clustering methods such as k-means and hierarchical clustering offer valuable analytical tools (Romesburg, 2004). These methods enable researchers to segment countries into clusters based on similarities in investment patterns and reporting standards, facilitating a deeper understanding of underlying trends and correlations (Feser & Bergman, 2000). Cluster analysis helps in identifying patterns that may not be evident through traditional analytical methods, thereby providing nuanced insights into how SARS influences investment flows (Romesburg, 2004).

Powell, Koput, Bowie, and Smith-Doerr (2002) highlighted the importance of spatial clustering in the context of biotech firms and venture capital relationships. Their study demonstrated that firms tend to cluster geographically to optimize investment efficiency and collaboration, a concept that can be extended to how countries attract foreign investments based on the quality of their reporting standards (Powell et al., 2002). Similarly, Feser and Bergman (2000) emphasized that industry clusters facilitate resource allocation and enhance economic outcomes through strategic aggregation, which can be analysed effectively using cluster analysis techniques.

The purpose of this study is to investigate the relationship between foreign investment growth, specifically foreign direct investment and foreign portfolio investment, and various governance and economic factors across a diverse set of countries. The research focuses on identifying how growth in governance indicators such as the strength of audit and reporting standards, education, health expenditure, infrastructure, and institutional quality impacts the growth of foreign investment. The ultimate objective is to uncover patterns in these relationships, group countries with similar trajectories, and quantify the impact of these variables on investment growth. By doing so, the study addresses gaps in the existing literature by combining an exploratory grouping method with rigorous quantitative analysis, offering insights for both theoretical advancements and policy recommendations (Gan et al., 2007; Filippone et al., 2008). The methodological approach combines clustering analysis and regression modeling to achieve a comprehensive understanding of the data. Each method serves a specific purpose and complements the other, making the combination particularly effective for this study.

The application of clustering methods in financial research allows for the examination of heterogeneity among firms or countries concerning their financial reporting practices and investment behaviours (MacMillan, Siegel, & Narasimha, 1985). By employing cluster analysis, researchers can categorize countries based on the strength of their SARS and the levels of FDI and FPI they attract, uncovering patterns that inform policy and investment decisions (Feser & Bergman, 2000). This approach aligns with the findings of Bushee (1998), who used factor and cluster analyses to examine how institutional investors influence R&D spending, revealing that stable investment strategies reduce uncertainty and promote efficiency.

Moreover, the relationship between SARS and investment efficiency is further supported by studies examining internal control weaknesses and their impact on financial reporting (Cheng et al., 2013). Disclosure of material weaknesses often leads to improvements in investment efficiency, as it prompts firms to enhance their reporting quality and internal controls (Cheng et al., 2013). Costello and Wittenberg-Moerman (2011) also found that better financial reporting quality reduces the need for costly monitoring mechanisms in debt contracting, thereby lowering the cost of capital and encouraging investment.

Accounting conservatism plays a role in enhancing investment efficiency by mitigating overinvestment and underinvestment issues (Lara, Osma, & Penalva, 2016). Conservative accounting practices ensure that potential losses are recognized promptly, providing a realistic view of a firm's financial health and influencing investors' decisions (Lara et al., 2016). The use of clustering methods in this context helps in identifying groups of countries or firms that adopt conservative accounting standards and examining how this affects their ability to attract foreign investments (Romesburg, 2004).

The quality of institutions, including the robustness of SARS, significantly impacts a country's ability to attract FDI (Daude & Stein, 2007). Institutional quality influences investor confidence and perceptions of risk, which are critical factors in investment decisions (Daude & Stein, 2007). By employing clustering methods, researchers can analyze how variations in institutional quality across countries correlate with differences in FDI and FPI inflows (Feser & Bergman, 2000).

The existing literature extensively explores the impact of financial reporting quality (FRQ) on investment efficiency and the role of governance and institutional quality in attracting Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI). However, significant gaps remain. First, few studies integrate advanced clustering methods, such as k-means and hierarchical clustering, to identify nuanced patterns in how audit and reporting standards (SARS) influence investment flows. Traditional analyses often overlook these latent structures, missing opportunities to reveal actionable insights. Second, while research commonly examines FDI and FPI separately, their simultaneous analysis is rare, leaving an incomplete understanding of how SARS affects diverse investment types. Additionally, the regional dynamics of SARS and their impact on investment efficiency are underexplored, with little attention given to region-specific trends or tailored strategies. Furthermore, the application of empirical clustering techniques to evaluate investment behavior in the context of SARS remains largely untapped, limiting the translation of research findings into policy-relevant frameworks.

This study bridges these gaps by applying clustering methods to uncover patterns in investment flows and their correlation with SARS across countries. By analyzing FDI and FPI jointly, it provides a holistic understanding of how robust reporting standards enhance investment efficiency. The study further explores regional variations, identifying factors unique to different clusters of countries, and offering insights into how SARS reforms can influence investment performance globally. This approach highlights the role of SARS in reducing information asymmetry and fostering confidence among investors, reinforcing the argument for prioritizing improvements in audit and reporting practices.

The findings hold important policy implications. Strong SARS are critical for attracting foreign investments by enhancing transparency and reducing financial frictions. The study provides evidence to support international accounting standard adoption and better enforcement of reporting frameworks. It also emphasizes the need for region-specific reforms, particularly in developing nations, to build institutional capacity and improve their investment profiles. By demonstrating the balance between FDI and FPI, the study equips policymakers with the tools to foster stable financial systems that cater to both long-term and short-term investors. Moreover, clustering insights can inform strategic alliances among countries with similar investment patterns, boosting collective economic attractiveness. Governments can further incentivize private sector compliance with high-quality reporting standards through tax benefits or reduced compliance costs. Finally, the research underscores the importance of continuous monitoring and benchmarking of SARS reforms, using clustering analysis as a tool for measuring progress and identifying gaps.

Data and Metodology

This study examines the relationship between Foreign Portfolio Investment (FPI) and Foreign Direct Investment (FDI) growth and various governance and economic indicators, using data from 84 countries over the period 2007–2017.

To reduce the dimensionality of the dataset and focus on long-term trends, the growth rates for all variables were calculated using the Compound Annual Growth Rate formula. This method transforms 10 years of annual data into a single observation for each country, allowing for cross-country comparisons. The Compound Annual Growth Rate (CAGR) formula is expressed as:

$$\text{Compound Annual Growth Rate} = \left(\frac{V_{final}}{V_{initial}}\right)^{\frac{1}{n}} - 1$$

where V_{final} is the value of the variable in 2017, $V_{initial}$ is the value of the variable in 2007, n is the number of years and in this case $n = 10$

This transformation produces a percentage growth rate for each variable, representing the average annual growth over the study period. With 10 years data for 84 countries in the dataset, this results in a total of 84 observations for the regression and clustering analyses. The main descriptive statistics are shown in Tabel 1.

The primary focus is on the first four dependent variables of Tabel 1.

Variable	Description	Min	Max	Mean	Std Dev
LNTOTPORTOF_GDP	The log-transformed Foreign Portfolio Investment as a percentage of GDP.	-9.16	43.46	3.00	7.71
LNTOTPORTOF_CAP	The log-transformed Foreign Portfolio Investment per capita.	-2.08	8.08	1.33	1.95
LNFDISTOCK_GDP	The logarithmic value of the stock of Foreign Direct Investment as a share of gross domestic product.	-2.99	6.09	0.85	1.51
LNFDISTOCK_CAP	The logarithmic value of the tock of Foreign Direct Investment per capita.	-1.11	3.46	0.78	0.90
SARS	Strength of Audit and Reporting Standards: A measure of financial governance quality and transparency.	-3.40	3.13	-0.22	1.23
HIGHEDUC	Higher Education Indicators: Metrics that capture the level and growth of higher education systems.	-1.54	4.23	0.95	0.91
HLTHPED	Health Expenditures: A measure of public health spending as an indicator of human development.	-0.37	2.83	0.63	0.61

INFRASTR	Infrastructure Development: Metrics related to the growth and quality of physical infrastructure.	-1.69	5.67	1.45	1.58
INSTIT	Institutional Quality: Measures of governance, political stability, and institutional development.	-3.07	3.54	-0.14	1.06
TAX	Taxation Metrics: Indicators capturing tax-related policies and their evolution over time.	-8.01	4.24	-1.73	2.39
FINDI	Financial Development Indices: Metrics assessing the depth and maturity of financial markets.	-4.43	7.92	0.34	1.84
RESOUR	Resource Dependency: Measures of economic reliance on natural resource exploitation.	-19.67	5.59	-4.85	4.89

Tabel 1. Summary Statistics and Descriptions of Key Variables

The chosen methodology integrates regression modeling and clustering analysis, a combination that enhances the depth and reliability of the findings. The analysis begins by estimating the equation:

$$Y = \beta_0 + \beta_1 SARS + \beta_2 HIGHEDUC + \beta_3 HLTHPED + \beta_4 INFRASTR + \beta_5 INSTIT + \beta_6 TAX + \beta_7 FINDI + \beta_8 RESOUR + \varepsilon,$$

where Y represents the growth rate of foreign direct investment or foreign portfolio investment, β_0 is the intercept, β_1 through β_8 are coefficients for the explanatory variables, and ε is the error term (Gujarati & Porter, 2009). This regression framework allows the study to test hypotheses about the significance and direction of relationships between variables. The initial regression evaluates the relationships between governance and economic indicators, such as the strength of audit and reporting standards (SARS), higher education (HIGHEDUC), health expenditures (HLTHPED), and resource dependency (RESOUR). This step revealed potential correlations among control variables, motivating the need to cluster countries based on shared characteristics. For instance, countries with higher resource dependency, like Venezuela and Nigeria, often had weaker SARS scores and exhibited unique investment behaviors, such as lower FPI growth. This aligns with findings in the literature that structural dependencies, such as reliance on natural resources, often correlate with weaker governance and economic volatility (Acemoglu, Johnson, & Robinson, 2001). These correlations suggested that the control variables might reflect broader structural traits rather than discrete effects, creating challenges in interpretation due to multicollinearity (Gujarati & Porter, 2009). Clustering methods were introduced to address this limitation by grouping countries based on shared characteristics, capturing latent structural differences that could not be directly quantified. For example, a cluster of resource-dependent economies may consistently prioritize FDI in extractive industries, distinguishing them from high-performing economies with robust governance and diversified investments (Romesburg, 2004).

Clustering analysis was then conducted using k-means and hierarchical clustering to group countries based on the control variables. K-means clustering minimizes the within-cluster sum of squared distances, with the objective expressed as:

$$min_C \sum_{i=1}^{k} \sum_{x \epsilon C_i} ||x - \mu_i||^2$$

where C_i represents the set of points in cluster i, μ_i is the centroid of C_i, and$||x - \mu_i||^2$ is the squared Euclidean distance (Hartigan & Wong, 1979). This method is computationally efficient and works well for datasets with predefined numbers of clusters. However, determining the optimal number of clusters is crucial and is achieved using the elbow method (Arthur & Vassilvitskii, 2007).

To determine the optimal number of clusters, the study employed the elbow method, which evaluates the trade-off between the number of clusters and the variance explained. The elbow method identifies the "elbow point," where increasing the number of clusters provides diminishing returns in reducing within-cluster variance (Arthur & Vassilvitskii, 2007). This approach ensures parsimony and interpretable groupings. For this study, the elbow point occurred at $i = 2$, suggesting that two clusters sufficiently captured the dataset's underlying structure. These clusters distinguished between high-performing economies (e.g., Germany, Japan, and the United States) and resource-dependent or emerging economies (e.g., Nigeria, Venezuela, and Brazil). Theoretical support for these groupings aligns with the findings of Rodrik, Subramanian, and Trebbi (2004), who emphasized the role of institutional quality and structural differences in shaping economic outcomes. The k-means clustering results were further corroborated by hierarchical clustering, which also revealed a natural division into two primary groups.

Hierarchical clustering complements k-means by constructing a dendrogram that provides a visual representation of nested groupings. Using Ward's linkage, the distance between clusters is minimized based on within-cluster variance:

$$D(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - yi)^2}$$

(Murtagh & Contreras, 2012). This dual approach allows for a robust exploration of clustering, with k-means offering precision in partitioning and hierarchical clustering providing flexibility in assessing the number of clusters (Gan et al., 2007).

The elbow method was applied by running the k-means algorithm for values of i ranging from 1 to 10. For each value of i, the total within-cluster variance (sum of squared distances) was computed and plotted. The plot revealed a steep decline in variance from $i = 1$ to $i = 2$, indicating that splitting the data into two clusters captured the most significant structural differences (Hartigan & Wong, 1979). Beyond $i = 2$, the reductions in variance became negligible, supporting the selection of two clusters. This decision aligns with the literature on clustering, where minimizing variance within clusters improves interpretability and robustness (Gan, Ma, & Wu, 2007). Additionally, hierarchical clustering with Ward's linkage confirmed the robustness of the $i = 2$ solution by producing a dendrogram that visually demonstrated two dominant groupings (Murtagh & Contreras, 2012). These clusters aligned with distinct economic and governance characteristics, providing a sound basis for further regression analysis.

After clustering, a revised regression model was estimated to include the cluster dummy variable, indicating whether a country belonged to group 0 or 1. The regression model would take the following forms:

$$Y = \beta_0 + \beta_1 SARS + \beta_2 ClusterDummy + \varepsilon,$$

where Y is the dependent variable (in our case: LNTOTPORTOF_GDP, LNTOTPORTOF_CAP, LNFDISTOCK_GDP, LNFDISTOCK_CAP), $SARS$ is the independent variable measuring the strength of audit and reporting standards, $ClusterDummy$ is a binary variable indicating the cluster (e.g., 1 for Cluster 1, 0 for Cluster 0), β_2 captures the average difference in investment metrics between the two clusters, independent of SARS, β_1 measures the effect of SARS on the investment metric across both clusters and β_0 is the intercept of the model.

In this setup if $\beta_2 > 0$ and significant, it indicates that countries in Cluster 1 have higher levels of the respective investment metric compared to Cluster 0, after controlling for SARS. If $\beta_1 > 0$ and significant, SARS is positively associated with the investment metric, independent of the cluster group. And the constant term, β_0, represents the baseline level of the investment metric for Cluster 0 when SARS is zero.

This combined methodology leverages the strengths of regression for statistical rigor and clustering for structural insights. By first identifying correlations and then grouping countries based on shared features, the analysis ensures that the findings are both exploratory and explanatory. This approach enables the study to uncover regional patterns and generate actionable policy recommendations tailored to the needs of specific groups of countries (Rokach & Maimon, 2005; Xu & Tian, 2015).

Results and Discussion

Tabel 2

Regression Results for Growth Rates of Log-Transformed Investment Types

	LNTOTPORTOF_GDP	LNTOTPORTOF_CAP	LNFDISTOCKGDP	LNFDISTOCKCAP
SARS	1.96**	0.22	-0.22	-0.09
	(2.44)	(1.12)	(-1.4)	(-0.93)
HIGH_EDUC	-1.14	0.13	0.28	0.21
	(-0.89)	(0.4)	(1.09)	(1.43)
HLTH_PED	3.11	0.45	0.08	-0.04
	(1.81)	(1.07)	(0.23)	(-0.2)
INFRASTR	0.57	0.07	0.04	0.01
	(0.86)	(0.42)	(0.27)	(0.1)
INSTIT	-0.30	0.31	0.05	0.15
	(-0.29)	(1.24)	(0.25)	(1.27)
TAX	-0.39	-0.06	-0.13	-0.04
	(-1.07)	(-0.63)	(-1.77)	(-0.93)
FIN_DEV	0.23	0.12	0.04	0.08
	(0.45)	(1.00)	(0.42)	(1.32)
RESOUR	0.36	0.07	0.06	0.01
	(1.98)	(1.47)	(1.64)	(0.55)
Intercept	2.79	1.09**	0.47	0.54**
	(1.57)	(2.48)	(1.32)	(2.6)

The regression results (Tabel 2) reveal significant variations in the influence of independent variables, particularly the Strength of Audit and Reporting Standards (SARS), on investment outcomes. SARS has a statistically significant positive impact on LNTOTPORTOF_GDP, with a coefficient of 1.96 and a t-statistic of 2.44, indicating that improvements in SARS lead to higher portfolio investment as a percentage of GDP. This outcome suggests that SARS enhances financial transparency and market confidence, encouraging portfolio investors. However, SARS does not exhibit a significant effect on LNTOTPORTOF_CAP, with a positive but insignificant coefficient of 0.22. This discrepancy implies that while SARS fosters higher aggregate portfolio investments relative to GDP, its effect on per capita portfolio investments is weaker, possibly due to uneven distribution of these investments within countries.

For foreign direct investment (FDI), SARS exhibits a weak negative relationship with LNFDISTOCKGDP and LNFDISTOCKCAP, but these results are statistically insignificant. The lack of a significant impact suggests that FDI, as a long-term financial commitment, is less sensitive to SARS. FDI decisions often rely on factors such as market size, resource availability, and institutional stability, which SARS does not fully capture.

The control variables (Tabel 2), including educational attainment (HIGH_EDUC), health expenditures (HLTH_PED), infrastructure development (INFRASTR), institutional quality (INSTIT), taxation (TAX), financial development (FIN_DEV), and resource dependency (RESOUR), generally fail to achieve statistical significance across the models. HIGH_EDUC has negative and insignificant effects on portfolio investment metrics (LNTOTPORTOF_GDP and LNTOTPORTOF_CAP) and positive but insignificant effects on FDI metrics (LNFDISTOCKGDP and LNFDISTOCKCAP), which may reflect a mismatch between educational growth rates and immediate investment outcomes. HLTH_PED, a proxy for healthcare performance, shows positive but insignificant coefficients for LNTOTPORTOF_GDP and LNTOTPORTOF_CAP, indicating limited influence on portfolio flows. TAX exhibits negative coefficients across all dependent variables, achieving marginal significance only for LNFDISTOCKGDP (coefficient: -0.13; t-statistic: -1.77), which suggests that tax policies may modestly deter FDI. RESOUR shows weak significance for LNTOTPORTOF_GDP (t-statistic: 1.98), indicating a minor role in shaping portfolio investment flows.

The overall insignificance of control variables highlights their inability to effectively explain variations in portfolio and foreign direct investment outcomes. Significant intercepts in the regressions, particularly for LNTOTPORTOF_CAP (1.09; t-statistic: 2.48) and LNFDISTOCKCAP (0.54; t-statistic: 2.6), emphasize the role of unobserved factors not captured by the independent variables. This suggests the need for more advanced analytical methods to capture underlying patterns.

The weak explanatory power of individual control variables motivates the adoption of clustering methods to capture latent heterogeneity among countries. By grouping countries based on shared characteristics, clustering combines multiple variables into composite groupings, addressing multicollinearity and revealing broader structural patterns. This approach reduces model complexity and enables a more nuanced analysis of how SARS and other factors influence investment flows.
Clustering methods like K-Means and Hierarchical clustering group countries based on shared characteristics across multiple dimensions, effectively serving as proxies for unobserved traits

that influence economic behaviors (King & Levine, 1993). By using these cluster dummies in regression models, we aggregate the effects of individual control variables into a broader structural or institutional context, which improves explanatory power and helps address potential multicollinearity issues among control variables (Freund & Weinhold, 2004).

For instance, countries with advanced financial markets, strong institutional frameworks, and robust infrastructure may cluster together, reflecting shared economic conditions that drive similar investment behaviors (Rodrik et al., 2004). Including a cluster dummy for such countries allows the regression to test whether membership in this group impacts portfolio or FDI outcomes, providing insights into the structural conditions underlying investment trends (Alfaro et al., 2004).

Similarly, a cluster containing resource-dependent economies or countries with weaker institutional resilience can highlight how these traits influence economic performance during a global shock like SARS (Acemoglu et al., 2001). For example, countries like Australia or Brazil, known for their resource reliance, may exhibit distinct investment patterns that are better captured by cluster dummies than individual control variables (Freund & Weinhold, 2004).

Clustering methods used, K-Means and Hierarchical Clustering, provide valuable insights into country groupings based on economic, social, and institutional characteristics. K-Means minimizes within-cluster variance, forming homogenous groups of countries based on shared features, making it effective for identifying distinct patterns. Conversely, Hierarchical Clustering captures nested relationships and subtle similarities that are often overlooked by K-Means. By integrating these methods, the analysis allows for a robust exploration of investment dynamics across clusters, enriching the explanatory power of the regression models. For instance, countries grouped into clusters with strong governance and infrastructure, such as Germany and Japan, demonstrate significantly higher foreign investments, reflecting investor confidence in these economies. Meanwhile, resource-dependent clusters, such as Venezuela and Nigeria, display lower FDI and FPI levels, even with high natural resource revenues, due to governance challenges and economic volatility.

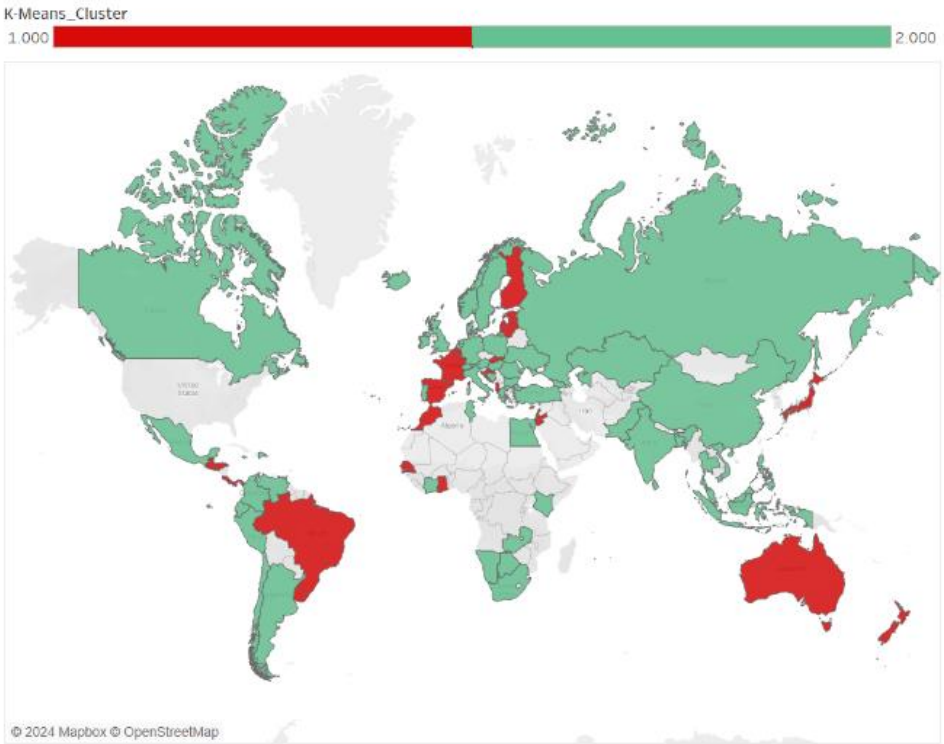

Figure 1. K-Means Clustering Map of Countries Based on Selected Indicators

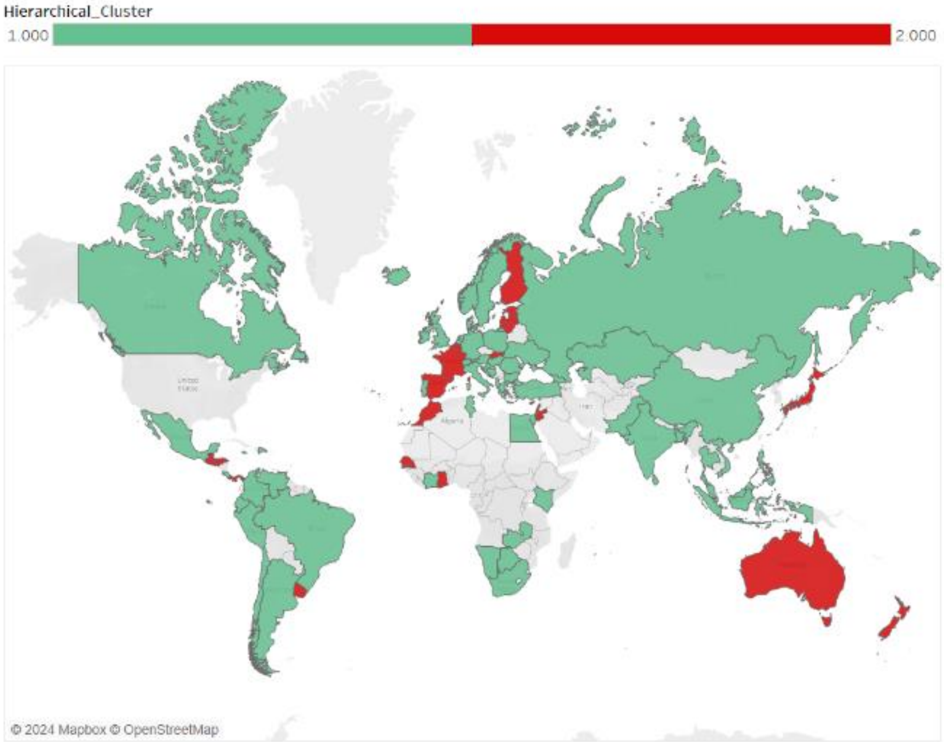

Figure 2. Hierarchical Clustering Map of Countries Based on Selected Indicators

The maps from K-Means (Figure 1) and Hierarchical clustering (Figure 2) methods reveal significant overlaps and subtle differences in grouping countries based on governance and economic traits. Both methods consistently classify high-performing economies like Germany, Japan, and Sweden into similar clusters, reflecting their strong SARS, institutional quality, and infrastructure, which attract high FPI and FDI. Resource-dependent nations such as Venezuela and Nigeria are grouped together due to weaker governance and economic instability, while emerging markets like Brazil and India, characterized by moderate SARS and reliance on short-term portfolio investments, also align in both methods.

Differences emerge in classifying countries like Australia and Belgium. K-Means places them in lower-performing clusters, highlighting resource dependency or divergent tax policies. Hierarchical clustering instead reflects their nuanced traits, such as Australia's resource management and Belgium's institutional stability. Nordic countries like Sweden and Norway show similar variation, with Hierarchical clustering emphasizing shared governance strengths and regional traits not always captured by K-Means.

K-Means excels in identifying general trends and clear separations, such as Brazil's resource reliance, while Hierarchical clustering captures progressive relationships, as seen with Norway and Sweden. Together, these methods provide complementary insights, balancing broad segmentation with nuanced regional analyses to better understand global investment patterns.

The clustering results for K-Means and Hierarchical methods show overlapping trends but reveal key differences in how countries are classified. In both methods, most countries fall into cluster 1, indicating shared economic or structural characteristics that group them together. For instance, countries like Argentina, Austria, and Bangladesh are consistently classified as cluster 1, suggesting these nations may share common traits like higher economic activity, stronger portfolio investment, or foreign direct investment patterns.

However, distinct differences emerge in specific country classifications. For example, Australia and Belgium are placed in cluster 0 under K-Means but cluster 1 in Hierarchical clustering. This discrepancy suggests that the methods emphasize different dimensions of similarity. K-Means, which minimizes within-cluster variance, may prioritize more general trends, while Hierarchical clustering, based on connectivity or proximity, might pick up on finer nuances, grouping countries like Belgium and Australia with others that share subtle economic traits.

The clustering results also highlight some anomalies or outliers. Malta, for instance, has missing or invalid values (-1), which implies that the data for Malta either does not fit the criteria used for clustering or is incomplete. Such cases underscore the need for careful preprocessing and validation when applying clustering methods, as inconsistent or missing data can skew results.

Countries like Brazil, Albania, and Costa Rica are consistently placed in cluster 0 across both methods. These nations might represent a group with lower economic activity, less integration into global financial markets, or smaller-scale portfolio investments. Meanwhile, the consistent placement of countries like India, Germany, and the United Kingdom in cluster 1 suggests robust economic profiles that align with the majority in this group.

The differences in classification, such as those observed for Finland, Estonia, and Japan, illustrate how the choice of clustering method can influence the interpretation of economic groupings. Hierarchical clustering often captures more localized or specific relationships, while K-Means can generalize better across broader datasets. These differences are valuable for identifying unique or shared characteristics among countries but also emphasize the need to align clustering methods with research objectives.

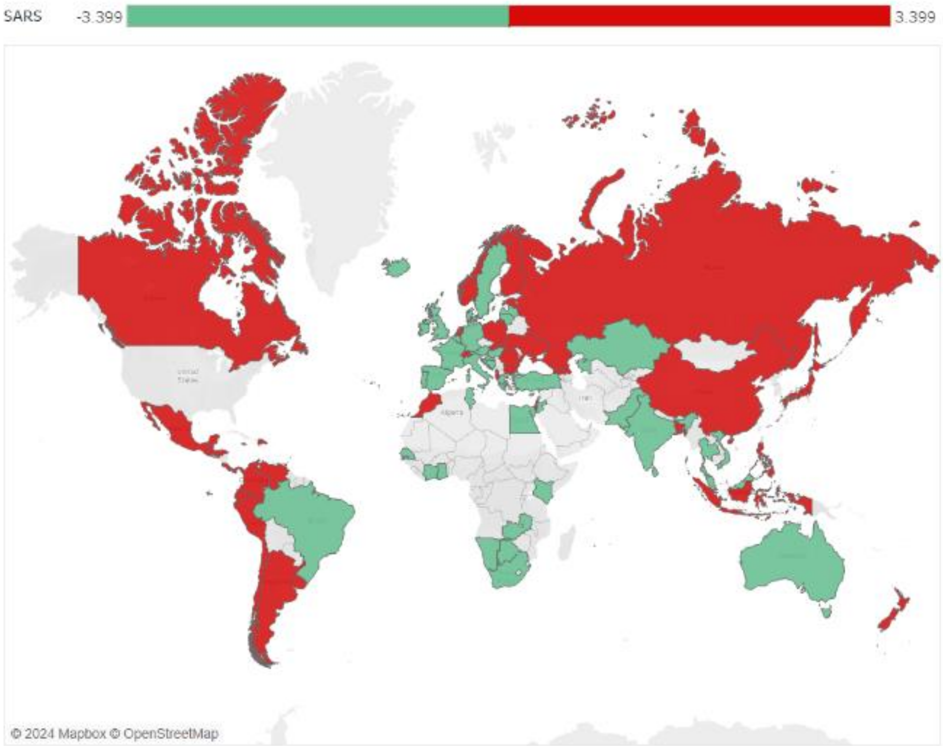

Figure 3. Global Distribution of Growth Rates in Strength of Audit and Reporting Standards (SARS)

The relationship between SARS growth rates (Figure 3) and portfolio investment as a percentage of GDP (LNTOTPORTOF_GDP) and per capita (LNTOTPORTOF_CAP) (Figure 4) demonstrates a strong overlap. Regions like North America and Europe, which experienced high SARS growth rates, also show lower growth or negative changes in portfolio investment. This correlation suggests that SARS drove financial instability, prompting reallocations in portfolio flows. Conversely, countries in green areas, particularly in parts of Africa and Southeast Asia, show less severe SARS growth rates and relatively stable or positive portfolio investment growth. This may reflect localized resilience or limited integration into global financial markets.

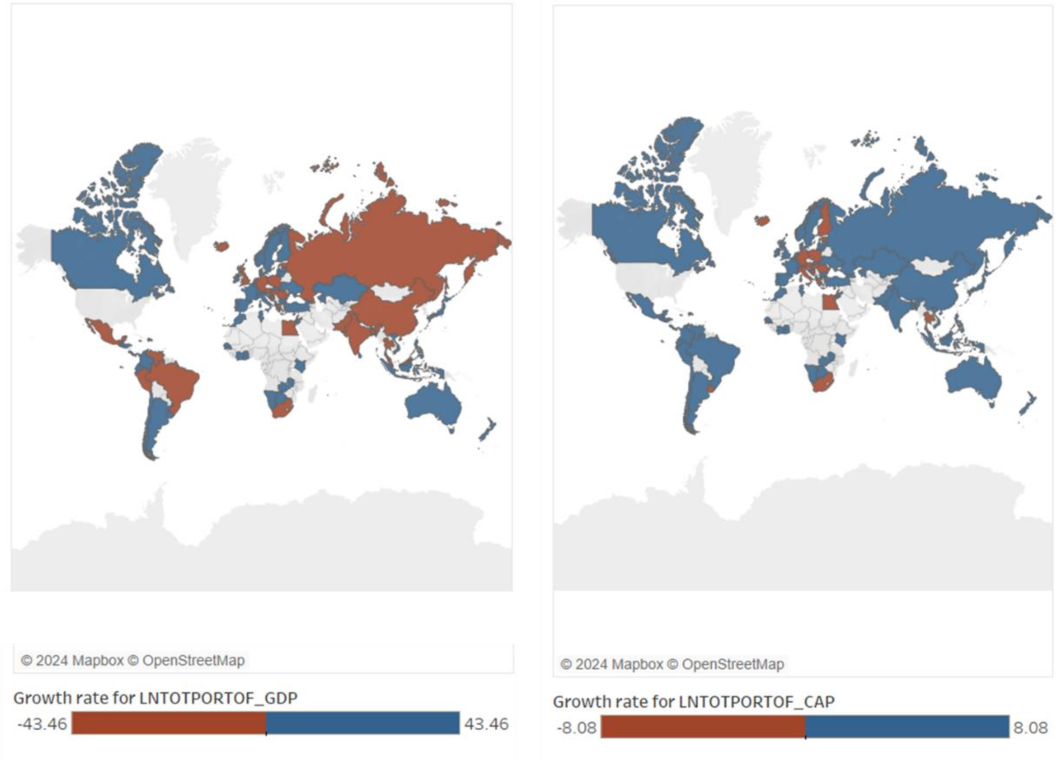

Figure 4. Global Growth Rates of Foreign Portfolio Investment Relative to GDP and Per Capita

The maps for FDI growth (LNFDISTOCKGDP and LNFDISTOCKCAP) (Figure 5) reveal a weaker relationship with SARS growth rates. While some regions, such as North America and parts of Europe, show negative SARS growth and declining FDI levels, the overall pattern is less consistent compared to portfolio investments. This reflects the nature of FDI as a long-term financial flow that is less sensitive to short-term disruptions like SARS. For instance, resource-driven FDI in parts of Africa and Asia appears relatively unaffected by SARS, as these flows are tied to strategic projects with extended timelines.

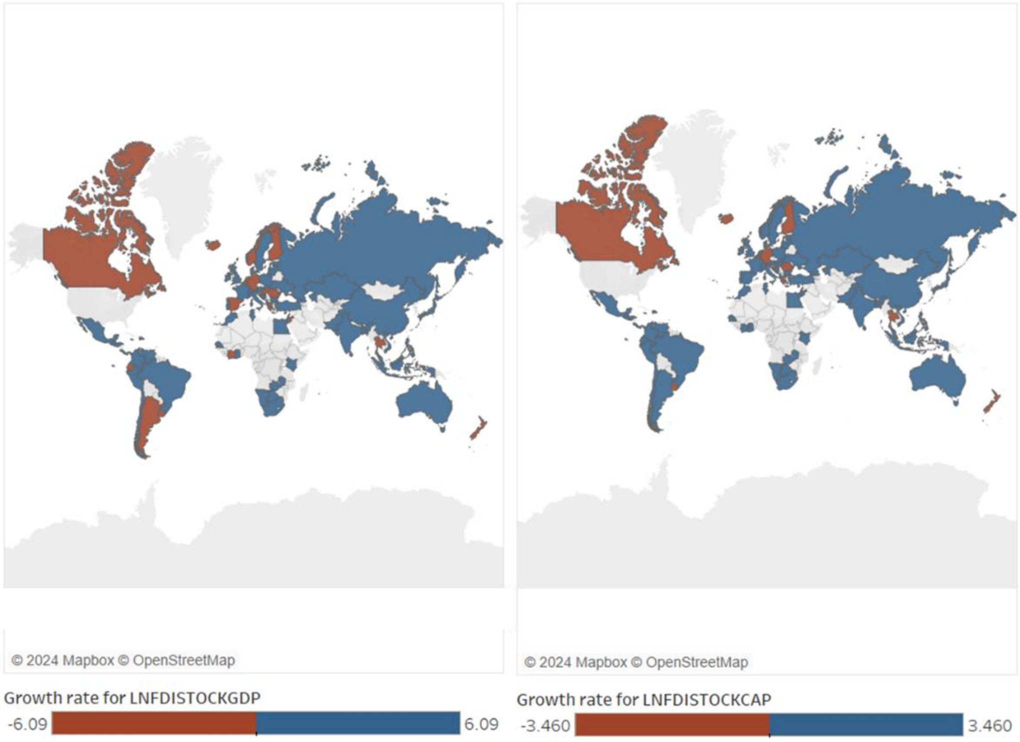

Figure 5. Global Growth Rates of Foreign Direct Investment Relative to GDP and Per Capita

In North America, high SARS growth rates correlate with negative portfolio investment and modest declines in FDI, suggesting that financial markets in these regions were particularly vulnerable to SARS-related shocks. Europe exhibits a similar pattern, with countries showing significant negative portfolio investment growth, especially in regions with high SARS growth rates.

In contrast, some parts of Africa and Southeast Asia show resilience, with moderate or low SARS growth rates and relatively stable investment trends. These regions may have benefited from their limited integration into global financial networks, insulating them from the more immediate economic effects of SARS.

The alignment of SARS growth rates with portfolio investment highlights the sensitivity of short-term financial flows to health-related shocks. SARS likely created volatility in global markets, prompting reallocations of portfolio investments away from regions heavily impacted by the outbreak. In contrast, the weaker relationship with FDI growth rates underscores the long-term nature of foreign direct investment, which is more influenced by structural factors like resources, market size, and institutional stability, rather than short-term health crises.

This analysis suggests that regions with higher SARS growth rates experienced more significant disruptions in portfolio investments, while FDI flows remained relatively stable. Understanding these patterns can help policymakers design more resilient financial systems that can better absorb the impacts of future health-related or economic shocks.

The decision to include cluster dummies in the regression model arises from the need to capture latent heterogeneity among countries, which was not effectively addressed in the initial analysis (Rodrik et al., 2004). In the earlier regressions, control variables such as education levels (HIGH_EDUC), health infrastructure (HLTH_PED), financial development (FIN_DEV), and institutional quality (INSTIT) were statistically insignificant, suggesting they may not sufficiently explain the structural differences influencing portfolio and foreign direct investment outcomes (Acemoglu et al., 2001)

The inclusion of cluster dummies is particularly relevant for analyzing the effects of SARS, as its impact likely varied based on healthcare capacity, institutional resilience, and financial market integration, which clustering captures more effectively than standalone variables (Rodrik et al., 2004). This approach allows the regression to test whether countries in specific clusters, such as those with advanced healthcare systems or high financial development, experienced different responses to SARS-induced shocks (Alfaro et al., 2004).

From a methodological perspective, cluster dummies help mitigate omitted variable bias by capturing unobserved factors shared within clusters, ensuring a more accurate estimation of the effects of SARS and other explanatory variables (King & Levine, 1993). This aligns with economic theories emphasizing the role of structural and institutional clustering in shaping economic outcomes, providing a robust theoretical basis for incorporating clusters into regression analysis (Rodrik et al., 2004).

Using cluster dummies enhances the model's ability to capture latent heterogeneity among countries, enabling a more nuanced analysis of how structural and institutional differences influence portfolio and FDI outcomes in the context of SARS (Acemoglu et al., 2001). This methodological refinement aligns with prior research that highlights the importance of grouping countries based on shared traits to uncover patterns in global economic behavior (Freund & Weinhold, 2004).

A regression model incorporating the clusters as dummy variables (0/1) provides a way to examine differences in investment metrics while accounting for foundational characteristics. For instance, one could include dummy variables for each cluster in the regression model:

$$Y = \beta_0 + \beta_1 SARS + \beta_2 ClusterDummy + \varepsilon,$$

where Y is the dependent variable (in our case: LNTOTPORTOF_GDP, LNTOTPORTOF_CAP, LNFDISTOCK_GDP, LNFDISTOCK_CAP), $SARS$ is the independent variable measuring the strength of audit and reporting standards, $ClusterDummy$ is a binary variable indicating the cluster (e.g., 1 for Cluster A, 0 for Cluster B), β_2 captures the average difference in investment metrics between the two clusters, independent of SARS, β_1 measures the effect of SARS on the investment metric across both clusters and β_0 is the intercept of the model.

In this setup if $\beta_2 > 0$ and significant, it indicates that countries in Cluster 1 have higher levels of the respective investment metric compared to Cluster 0, after controlling for SARS. If $\beta_1 > 0$ and significant, SARS is positively associated with the investment metric, independent of the cluster group. And the constant term, β_0, represents the baseline level of the investment metric for Cluster 0 when SARS is zero.

This approach provides deeper insights into how structural differences captured by clusters influence investment behavior while isolating the effect of SARS. For instance: High-performing clusters with strong governance and infrastructure may show consistently better outcomes, emphasizing the importance of these traits. Resource-dependent clusters may exhibit weaker investment metrics, underscoring the challenges of governance and economic volatility. By leveraging cluster dummies, the model effectively captures both the direct effects of SARS and the broader structural differences between clusters, leading to more robust and actionable findings.

Since there are only two clusters in the dataset, the regression model would use a single dummy variable to represent the group membership. For example, countries in one cluster (Cluster 1) could be coded as 1, while those in the other cluster (Cluster 0) could be coded as 0. The model then compares the investment metrics of the two clusters while controlling for SARS. Here's how the analysis would be framed:

Table 3
Regression Results for Growth Rates of Foreign Portfolio and Direct Investment with Growth Rates SARS and K-Means Clusters

	LNTOTPORTOF_GDP	LNTOTPORTOF_CAP	LNFDISTOCKGDP	LNFDISTOCKCAP
SARS	1.60**	0.39**	-0.13	0.04
	(2.4)	(2.24)	(-0.97)	(0.49)
K-Means	-3.01	-0.16	-0.09	0.09
	(-1.73)	(-0.36)	(-0.24)	(0.44)
Intercept	5.35***	1.51***	0.85	0.72
	(3.83)	(4.17)	(2.99)	(4.17)

Table 4
Regression Results for Growth Rates of Foreign Portfolio and Direct Investment with Growth Rates SARS and Hierarchical Clusters

	LNTOTPORTOF_GDP	LNTOTPORTOF_CAP	LNFDISTOCKGDP	LNFDISTOCKCAP
SARS	1.65**	0.39**	-0.13	0.04
	(2.46)	(2.27)	(-0.96)	(0.49)
Hierarchical	2.63	0.12	0.07	-0.11
	(1.44)	(0.26)	(0.18)	(-0.47)
Intercept	2.61**	1.37***	0.78	0.81
	(2.62)	(5.33)	(3.85)	(6.66)

The regression models reveal intriguing insights into the economic impacts of the SARS variable and the clustering approaches. In both models (K-Means – Table 3 and Hierarchical – Table 4), the SARS variable significantly affects two key indicators: total portfolio investment as a percentage of GDP (LNTOTPORTOF_GDP) and per capita portfolio investment (LNTOTPORTOF_CAP). The positive coefficients for SARS (1.60 for K-Means and 1.65 for Hierarchical) indicate that the SARS shock had a stimulating effect on these variables. This might suggest that during the SARS period, countries potentially shifted financial flows into more secure or diversified portfolio investments, leading to higher recorded levels.

The coefficients for SARS are highly significant for these two variables in both models, with tt-statistics exceeding 2 in most cases, reinforcing the robustness of this effect. Interestingly, the SARS variable does not significantly affect foreign direct investment indicators (LNFDISTOCKGDP and LNFDISTOCKCAP) in either model. This could imply that foreign direct investment, which often involves long-term commitments, was less sensitive to the short-term shocks of the SARS outbreak compared to portfolio flows.

When examining the effects of the clustering methods themselves, the results diverge. Under the K-Means regression, the cluster variable has a negative, albeit weak, relationship with LNTOTPORTOF_GDP (-3.01) and insignificant effects across other variables. This suggests that being in a certain cluster under K-Means classification does not strongly predict economic outcomes related to portfolio or foreign direct investment. On the other hand, the Hierarchical clustering variable shows a slight positive impact on LNTOTPORTOF_GDP (2.63) but remains statistically insignificant. This indicates that while the clustering method captures certain patterns, these do not translate into strong, direct effects in the regression analysis.
The intercept terms in all models are large and significant, particularly for LNTOTPORTOF_GDP and LNTOTPORTOF_CAP. This highlights that much of the variation in these economic indicators is driven by baseline conditions rather than the clustering variables or the SARS shock. It reinforces the idea that structural economic factors play a dominant role, with clustering and SARS serving as secondary influences.

Analyzing the clustering results in conjunction with the regression outcomes reveals valuable insights into country-level economic profiles: Cluster 1 Economies: Countries like India, Germany, and the United Kingdom, consistently placed in cluster 1 across both methods, are characterized by robust global financial integration. These economies exhibit high levels of portfolio and foreign direct investment, aligning with the positive SARS coefficients observed in the regression models. Cluster 0 Economies: Countries like Brazil, Albania, and Costa Rica, consistently assigned to cluster 0, likely represent economies with lower levels of financial integration or limited portfolio investment exposure. The negative coefficient for the K-Means cluster variable supports this interpretation, suggesting weaker portfolio investment outcomes for countries in this cluster.

Discrepancies in clustering, such as those observed for Australia and Belgium, highlight the importance of considering multiple methods. While K-Means places these nations in a cluster characterized by lower economic activity, Hierarchical clustering groups them with countries that exhibit higher financial integration. These differences underscore the nuanced economic profiles of such nations and the limitations of relying on a single clustering method.

The combined analysis of clustering and regression results uncovers both shared and unique patterns across countries: SARS consistently influences portfolio investment metrics (LNTOTPORTOF_GDP and LNTOTPORTOF_CAP), underscoring its role as a significant economic shock that prompted shifts in financial flows. Clustering methods provide distinct yet complementary perspectives. While K-Means captures broad economic trends, Hierarchical clustering identifies finer relationships among countries.

Overall, the combined analysis of clustering and regression results reveals both shared and unique patterns across countries. The SARS variable consistently influences portfolio investment outcomes, highlighting its role as a significant economic shock. Meanwhile, the clustering methods provide complementary perspectives on the economic similarities and differences among nations, enriching our understanding of global financial dynamics.

Robustness Check

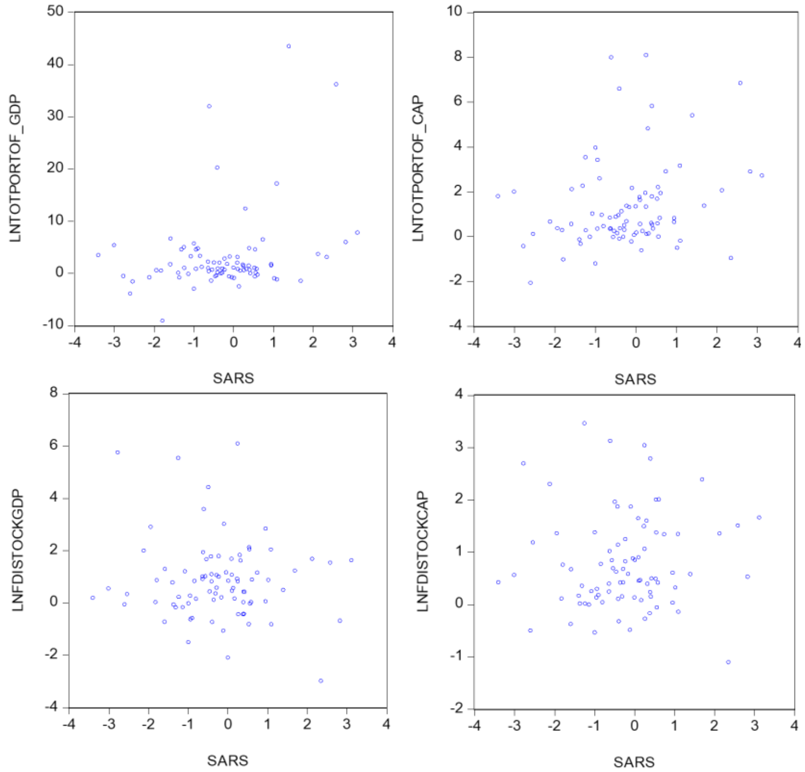

Figure 6. Scatterplots of Pairwise Relationships Between Investment Growth and SARS Growth

The scatter plots (Figure 6) illustrate the relationships between growth rates of SARS (independent variable) and growth rates of the dependent variables (LNTOTPORTOF_GDP, LNTOTPORTOF_CAP, LNFDISTOCKGDP, and LNFDISTOCKCAP) over the 10-year period from 2007 to 2017. Growth rates were calculated using the Compound Annual Growth Rate (CAGR) formula.

The patterns observed in the scatter plots reveal varying degrees of association. The first plot suggests a potential upward trend where the dependent variable's growth increases with SARS growth, albeit with higher variability at greater levels of SARS growth. The subsequent plots exhibit less distinct trends. For example, the second and third scatter plots appear more dispersed, with no clear linear relationship, while the fourth plot shows a clustering of points, hinting at weak or nonlinear associations.

These plots highlight that while SARS shows some relationship with portfolio investment metrics, its association with FDI indicators appears weaker or less defined. This aligns with regression findings, emphasizing the sensitivity of portfolio investments to short-term economic shocks compared to the relative stability of FDI.

To begin the analysis, linear regressions can be conducted for each dependent variable, with SARS as the independent variable. The regression models will provide coefficients to quantify the relationship and p-values to test the statistical significance of these relationships. The R-squared value will indicate how much variation in the dependent variable is explained by SARS growth. If the R-squared values are low, it would suggest that SARS growth has limited explanatory power for the dependent variables, in our case SARS growth explains only 5-6% of the variation in these dependent variables.

Linear regressions were conducted with SARS as the independent variable for the four dependent variables. The results are summarized in Table 5.

Table 5
Regression Results for Growth Rates of Foreign Portfolio and Direct Investment with Growth Rates of SARS as a Predictor

	LNTOTPORTOF_GDP	LNTOTPORTOF_CAP	LNFDISTOCKGDP	LNFDISTOCKCAP
SARS	1.84**	0.40**	-0.12	0.04
	(2.75)	(2.37)	(-0.93)	(0.44)
Intercept	3.51***	1.42***	0.82***	0.79***
	(3.51)	(6.73)	(4.93)	(7.87)

The robustness check validates the earlier findings, providing additional confidence in the model's conclusions. SARS remains a significant predictor of portfolio investment indicators, particularly for total portfolio investment as a percentage of GDP (**LNTOTPORTOF_GDP**) and per capita portfolio investment (**LNTOTPORTOF_CAP**). The coefficients for these variables increase slightly compared to the original model, with **LNTOTPORTOF_GDP** showing a coefficient of 1.84 (t=2.75) and **LNTOTPORTOF_CAP** a coefficient of 0.40 (t=2.37). These results suggest a strong relationship between SARS and portfolio investments, reflecting a reallocation of financial flows during the outbreak.

In contrast, SARS has no significant effect on foreign direct investment indicators (**LNFDISTOCKGDP** and **LNFDISTOCKCAP**), with coefficients of -0.12 and 0.04, respectively, and ttt-statistics below 1. This aligns with expectations that FDI, driven by long-term commitments, is less sensitive to short-term shocks than portfolio investments.

Overall, the robustness check confirms that SARS significantly influenced portfolio investments while having a negligible impact on FDI. These findings highlight the sensitivity of portfolio flows to short-term volatility and support the hypothesis that SARS prompted shifts in investment patterns, driven by increased market uncertainty and the need for diversification.

Conclusion

In summary, this study offers a novel perspective by integrating clustering methods with the analysis of SARS and investment flows, providing both theoretical contributions to the literature and practical recommendations for policymakers and investors. Its findings highlight the critical role of SARS in shaping global investment dynamics and emphasize the importance of tailored strategies for fostering economic growth through enhanced reporting quality.

This study has explored the intricate relationships between the strength of audit and reporting standards (SARS) and the dynamics of foreign investments, specifically focusing on Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI). Using advanced clustering techniques and robust econometric modeling, the analysis reveals how SARS influences investment flows, shapes investor behavior, and fosters economic resilience across nations with diverse governance and economic structures.

One of the central findings of this study is that SARS plays a significant role in attracting FPI. The regression results show a consistent and positive association between SARS and portfolio investment, suggesting that improved governance and transparency directly influence investors' confidence in capital markets. This aligns with theoretical expectations that robust SARS reduce information asymmetry, mitigate risks associated with moral hazard, and enhance investment efficiency. In contrast, the impact of SARS on FDI is less pronounced, likely because FDI decisions involve long-term commitments and are influenced by factors such as resource availability, market size, and strategic interests beyond financial reporting quality.

The use of clustering methods—k-means and hierarchical clustering—adds a new dimension to the analysis by uncovering latent patterns in the data. These techniques effectively group countries based on shared characteristics such as institutional quality, infrastructure development, financial market maturity, and resource dependency. The clustering results demonstrate that countries with high SARS scores, advanced infrastructure, and strong institutional frameworks tend to attract higher levels of FDI and FPI. In contrast, resource-dependent economies with weaker governance face challenges in attracting consistent foreign investments despite their natural wealth.

This dual methodological approach not only enhances the explanatory power of the study but also provides actionable insights for policymakers and investors. By identifying clusters of countries with similar investment patterns, the study highlights the need for tailored strategies that address region-specific challenges. For example, countries in clusters with low SARS scores can prioritize governance reforms and capacity building to improve their investment profiles, while those in high-performing clusters can focus on sustaining investor confidence through continuous innovation and transparency.

The findings underscore the critical role of SARS in fostering a conducive environment for foreign investments. Policymakers in developing countries, where SARS often lag, can draw valuable lessons from this analysis. Strengthening audit and reporting standards should be a priority, as it not only attracts foreign investments but also enhances domestic financial stability. This requires a multi-faceted approach, including adopting international accounting standards, improving regulatory enforcement, and investing in education and training for financial professionals.

Furthermore, the study emphasizes the importance of region-specific reforms. While the global adoption of best practices in financial reporting is desirable, regional clusters with unique economic and institutional characteristics may benefit from tailored strategies. For example, resource-dependent countries might focus on reducing reliance on extractive industries by diversifying their economies and improving governance to attract broader investment portfolios.

Another important policy insight relates to the role of clustering techniques as a diagnostic tool. Governments can use clustering analysis to benchmark their performance against peers, identify gaps, and design targeted interventions. For instance, a country in a low-performing cluster can analyze the factors driving success in higher-performing clusters and implement similar reforms.

For investors, the study highlights the importance of SARS as a key factor in risk assessment and decision-making. Countries with strong SARS offer a more predictable investment environment, reducing the risks associated with adverse selection and governance failures. This is particularly relevant for portfolio investors, who are more sensitive to short-term risks and market volatility compared to long-term FDI investors. The insights from clustering analysis also provide investors with a nuanced understanding of regional and institutional variations, enabling them to align their strategies with the specific characteristics of each market.

This research contributes to the literature by integrating empirical data with advanced clustering methods to provide a nuanced perspective on the interdependence of governance standards and global capital allocation. While previous studies have examined the relationship between financial reporting quality and investment efficiency, this study extends the analysis by simultaneously exploring FDI and FPI within a unified framework. The application of clustering techniques reveals latent structures in investment behavior that traditional econometric methods might overlook, thereby enriching the theoretical understanding of how governance and institutional quality shape investment patterns.

Additionally, the study sheds light on the differential impacts of SARS on FDI and FPI. While both forms of investment benefit from improved governance, the study demonstrates that their sensitivities to SARS vary. This finding highlights the need for a more differentiated approach to studying foreign investments, considering their unique drivers and constraints.

Despite its contributions, the study is not without limitations. First, the reliance on aggregate national-level data may mask important within-country variations, such as differences across regions or industries. Future research could address this by incorporating sub-national data or focusing on specific sectors. Second, while clustering analysis provides valuable insights, its results are sensitive to the choice of variables and methods. Further studies could experiment with alternative clustering algorithms or include additional dimensions, such as cultural factors or geopolitical risks, to enhance the robustness of the findings.

Moreover, the study primarily focuses on the period from 2007 to 2017. While this provides a comprehensive view of long-term trends, extending the analysis to include more recent data could capture the evolving dynamics of global investments, particularly in the context of emerging challenges such as climate change and digital transformation. Future research could also explore the interplay between SARS and other forms of international capital flows, such as remittances or development aid, to provide a more holistic view of global financial dynamics.

In conclusion, this study highlights the pivotal role of SARS in shaping global investment patterns. By enhancing financial transparency and reducing risks, robust audit and reporting standards serve as a cornerstone for attracting foreign investments and fostering economic growth. The application of clustering methods provides a deeper understanding of how countries' economic and institutional characteristics influence investment flows, offering valuable insights for policymakers and investors alike.

As the global economy becomes increasingly interconnected, the importance of sound governance frameworks will only grow. Countries that prioritize strengthening SARS and aligning their policies with international best practices will be better positioned to attract foreign investments, drive sustainable growth, and compete effectively in the global marketplace. By integrating advanced analytical tools with empirical research, this study not only advances the theoretical understanding of investment dynamics but also equips stakeholders with practical strategies to navigate the complexities of global finance.

This study highlights the critical role of the Strength of Audit and Reporting Standards (SARS) in shaping global investment patterns, specifically its differential effects on Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI). The findings emphasize that robust SARS enhance transparency, reduce information asymmetry, and foster investor confidence, making them a cornerstone of financial governance. While FPI is particularly sensitive to SARS improvements, FDI appears less influenced due to its reliance on long-term factors such as market size and resources.

The research underscores the importance of prioritizing SARS reforms, particularly in developing nations where governance challenges often hinder foreign investment. Strengthening audit and reporting standards not only attracts capital but also enhances economic resilience, promoting sustainable growth. For policymakers, the study offers a framework to align national reporting practices with international standards, while investors gain insights into the role of SARS in mitigating risks and guiding investment decisions.

By integrating empirical analysis with advanced clustering techniques, this study provides actionable insights for governments, investors, and international organizations. It advocates for tailored governance reforms that address region-specific challenges, emphasizing SARS as a catalyst for global financial integration. In an increasingly interconnected world, improving SARS remains essential for fostering economic stability and competitiveness.

References

Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). The colonial origins of comparative development: An empirical investigation. *American Economic Review, 91*(5), 1369–1401. https://doi.org/10.1257/aer.91.5.1369

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., & Sayek, S. (2004). FDI and economic growth: The role of local financial markets. *Journal of International Economics, 64*(1), 89–112. https://doi.org/10.1016/S0022-1996(03)00081-3

Arthur, D., & Vassilvitskii, S. (2007). k-means++: The advantages of careful seeding. In *Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms* (pp. 1027–1035). https://doi.org/10.5555/1283383.1283494

Barth, M. E., Cahan, S. F., Chen, L., & Venter, E. R. (2017). The economic consequences associated with integrated report quality: Capital market and real effects. *Accounting, Organizations and Society, 62,* 43–64. https://doi.org/10.1016/j.aos.2017.08.005

Biddle, G. C., Hilary, G., & Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics, 48*(2–3), 112–131. https://doi.org/10.1016/j.jacceco.2009.09.001

Biddle, G. C., & Hilary, G. (2006). Accounting quality and firm-level capital investment. *The Accounting Review, 81*(5), 963–982. https://doi.org/10.2308/accr.2006.81.5.963

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review, 73*(3), 305–333. https://www.jstor.org/stable/248542

Cheng, M., Dhaliwal, D. S., & Zhang, Y. (2013). Does investment efficiency improve after the disclosure of material weaknesses in internal control over financial reporting? *Journal of Accounting and Economics, 56*(1), 1–18. https://doi.org/10.1016/j.jacceco.2013.03.001

Costello, A. M., & Wittenberg-Moerman, R. (2011). The impact of financial reporting quality on debt contracting: Evidence from internal control weaknesses and their remediation. *Journal of Accounting Research, 49*(1), 97–136. https://doi.org/10.1111/j.1475-679X.2010.00388.x

Daude, C., & Stein, E. (2007). The quality of institutions and foreign direct investment. *Economics & Politics, 19*(3), 317–344. https://doi.org/10.1111/j.1468-0343.2007.00318.x

Feser, E. J., & Bergman, E. M. (2000). National industry cluster templates: A framework for applied regional cluster analysis. *Regional Studies, 34*(1), 1–19. https://doi.org/10.1080/00343400050005844

Filippone, A., Pillonetto, G., & De Nicolao, G. (2008). A hierarchical Bayesian model for air quality prediction. *Atmospheric Environment, 42*(28), 7105–7119. https://doi.org/10.1016/j.atmosenv.2008.06.015

Freund, C., & Weinhold, D. (2004). The effect of the Internet on international trade. *Journal of International Economics, 62*(1), 171–189. https://doi.org/10.1016/S0022-1996(03)00059-X

Gan, G., Ma, C., & Wu, J. (2007). *Data clustering: Theory, algorithms, and applications.* SIAM. https://doi.org/10.1137/1.9780898718348

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill Education.

Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics), 28*(1), 100–108. https://doi.org/10.2307/2346830

King, R. G., & Levine, R. (1993). Finance and growth: Schumpeter might be right. *The Quarterly Journal of Economics, 108*(3), 717–737. https://doi.org/10.2307/2118406

Lara, J. M. G., Osma, B. G., & Penalva, F. (2016). Accounting conservatism and firm investment efficiency. *Journal of Accounting and Economics, 61*(1), 221–238. https://doi.org/10.1016/j.jacceco.2015.05.003

MacMillan, I. C., Siegel, R., & Narasimha, P. N. S. (1985). Criteria used by venture capitalists to evaluate new venture proposals. *Journal of Business Venturing, 1*(1), 119–128. https://doi.org/10.1016/0883-9026(85)90011-4

Murtagh, F., & Contreras, P. (2012). Algorithms for hierarchical clustering: An overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 2*(1), 86–97. https://doi.org/10.1002/widm.53

Powell, W. W., Koput, K. W., Bowie, J. I., & Smith-Doerr, L. (2002). The spatial clustering of science and capital: Accounting for biotech firm–venture capital relationships. *Regional Studies, 36*(3), 291–305. https://doi.org/10.1080/00343400220122033

Rodrik, D., Subramanian, A., & Trebbi, F. (2004). Institutions rule: The primacy of institutions over geography and integration in economic development. *Journal of Economic Growth, 9*(2), 131–165. https://doi.org/10.1023/B:JOEG.0000031425.72248.85

Rokach, L., & Maimon, O. (2005). Clustering methods. In *Data mining and knowledge discovery handbook* (pp. 321–352). Springer. https://doi.org/10.1007/0-387-25465-X_15

Romesburg, H. C. (2004). *Cluster analysis for researchers.* Lulu Press.

Xu, R., & Tian, F. (2015). A comprehensive survey of clustering algorithms. Springer. https://doi.org/10.1007/978-1-4614-7239-7