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Exploring the evolving determinants of foreign direct investment and the investing country preferences in developing Asian economies using machine learning[1]

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[1] This contribution was prepared for the conference. The views expressed are those of the authors and do not necessarily reflect the views of the European Central Bank, the Bank of Spain, the BIS, the IFC or the other central banks and institutions represented at the event.

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Abstract

Foreign Direct Investment (FDI) has the potential to stimulate and sustain economic growth in both the recipient and investing countries, especially during the economic recovery following the pandemic. Recipient countries have been able to finance new infrastructure projects and create local jobs through FDI, while foreign direct investors have been able to enlarge their global presence. According to the UNCTAD World Investment Report 2023, Asia received 51% of global inflows but remained steady at USD 662 billion in 2021. Singapore, the largest receiver in Southeast Asia, set another record, increasing by 8% to $141 billion. Flows to Malaysia increased by 39% to $17 billion, setting a new high for the country. FDI to Vietnam and Indonesia increased by 14% and 4%, respectively, to $18 billion and $22 billion, while FDI to the Philippines decreased by 23% due to many divestments. There have been many studies done on the factors that influence FDI. However, more research is still needed to determine the factors that contribute to the increasing foreign capital transported and the preference of investing countries to Asia's developing markets. With the advent of automated machine learning (ML), we utilize panel data from several open-source international databases and run various ML techniques (e.g., Decision Trees, Random Forest Classifier, Gradient Boosting Machines) in examining the economic, institutional, political, and environmental determinants of FDI inflow from 2008 to 2022 in developing Asian Economies as well as uncover investing country preferences through time via unsupervised similarity calculations.

Keywords: foreign direct investment, developing Asia, machine learning, panel data analysis

JEL classification: F21, B17, G11, C33, O53

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Contents

1. Introduction

In the fast-evolving global economic landscape, it has been important to understand the drivers behind Foreign Direct Investment (FDI), especially for politicians, investors, and researchers. FDI significantly shapes the nations' economic future, impacting economic growth, employment, and technological progress (Alfaro et al., 2017). Conventional economic models and statistical research have been used to identify FDI determinants.

ML has been effective in finding patterns and connections within vast and complicated datasets, which is essential given the complexity and non-linearity of factors influencing FDI. As such, for this study, we used ML techniques to find new determinants, uncover hidden insights, and improve the predictive power of FDI models. The main objective of this research is to utilize ML techniques to bridge the gap between conventional econometric methodologies and the complex nature of FDI.

The ML methods used were decision trees, random forests, and gradient boosting to find non-linear correlations between FDI and its determinants. These models and algorithms can often achieve higher accuracy and generalization than linear models and algorithms, but they may also require more data, tuning, and interpretation. ML methods were also used to identify the relevance of various factors affecting FDI so as to provide insights into the variables most significantly influencing investment decisions.

Finally, we used unsupervised similarity calculations to uncover the similarity between country investors based on their interactions or preferences without relying on explicit labels or training data. To uncover mutual economic interests, geopolitical factors, or geographical preferences, we examined which countries invest together regularly or have comparable investment destinations.

We utilized an extensive dataset covering trade flows, institutional variables, macroeconomic indicators, and other pertinent variables of developing Asian nations over a predetermined period. We then compared the different ML algorithms with conventional econometric models in capturing the intricate dynamics of FDI.

2. FDI in developing Asia

It is crucial to investigate the factors influencing FDI in developing Asia and provide information to investors, researchers, and governments. This knowledge is essential for developing successful policies, attracting investments, fostering economic expansion, and ensuring long-term development.

Before the 1980s, developing countries viewed FDI adversely. This was fuelled by colonial experiences and the widespread belief that multinational corporations (MNCs) would wield significant economic and political power over the host country (Brooks et al., 2003). That perspective on FDIs has long been abandoned, with FDIs now viewed as a crucial driver of economic progress. China's Open Door Policy in 1978 was a pivotal event that transformed the global FDI landscape, marking China's transition towards an open-market economy by allowing foreign investments. Special Economic Zones (SEZ), free of bureaucratic restrictions and regulations, were quickly established in Shenzhen, Shantou, Zhuhai, and Xiamen, making China an attractive foreign investment destination. Since their inception, these SEZs have welcomed significant FDIs, paving the way for China's rapid industrialization and propelling the country to become the second largest economy in the world.

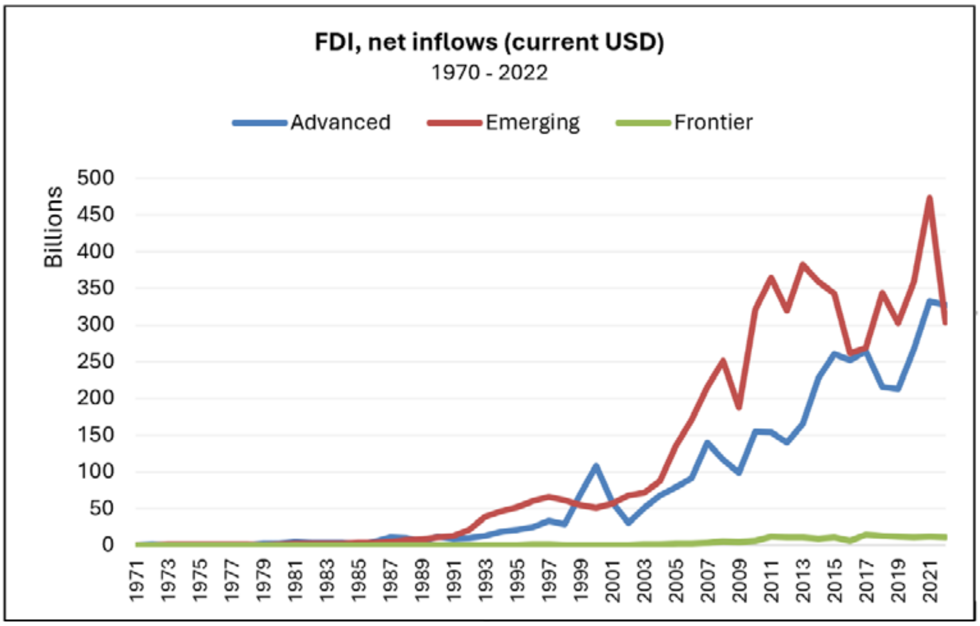

Figure 1. Sum of FDI net inflows (BoP, current USD)
Source: Authors' computation based on the World Development Indicators.

FDIs are regarded as critical in driving economic growth in China and the rest of Asia. Figure 1 demonstrates that net FDI inflows into Advanced and Emerging Asian countries have considerably increased since the 1970s.[2] For all of Asia, FDI inflows

[2] Per the IMF's Regional Economic Outlook, Advanced Asian countries include Australia, Hong Kong SAR, Japan, Korea, New Zealand, Singapore, and Taiwan Province of China; Emerging Asian countries are China, India, Indonesia, Malaysia, the Philippines, Thailand, and Vietnam; while, Frontier Asian countries are Bangladesh, Cambodia, Lao People's Democratic Republic, Mongolia, Myanmar, Nepal, and Sri Lanka.

began to climb in the late 1980s and have continued to increase since then, suggesting the region's positive disposition towards FDIs.

There are several reasons why a host country accepts FDIs. FDIs contribute to capital formation by injecting much-needed funds into domestic economies (Blomström & Kokko, 2003). This influx of capital encourages investment in various sectors and stimulates economic growth. FDIs are also crucial for technology transfer since multinational corporations bring innovative technologies and managerial expertise to the host country, thereby increasing the productivity and efficiency of local industries (Blalock & Gertler, 2008). The positive impact also extends to job generation since foreign investors often establish or expand businesses (Lipsey & Sjöholm, 2005).

Furthermore, FDIs improve market access and global competitiveness by allowing local industries to compete in foreign markets and increase exports (UNCTAD, 2020). FDI inflows also lead to the construction of critical infrastructure, such as transportation and energy, which improves the overall economic landscape of host nations (Asiedu, 2002). While the literature recognizes the varied nature of FDI effects, there is widespread consensus that well-managed and targeted foreign investments can significantly propel economic development.

Asian nations have adopted several reforms to create an inviting environment for foreign investors as the benefits of FDIs have become widely recognized. For instance, countries like Singapore and Hong Kong have demonstrated proficiency in liberalizing investment policies, offering minimum bureaucratic obstacles and expediting approval procedures for foreign investors. China and India have established SEZs that provide tax incentives and simplified regulations. Malaysia and Thailand leveraged tax incentives to attract FDI and reduced tax rates for a specified period to encourage foreign investments. At the same time, South Korea focused on infrastructure development, while Vietnam established Investment Promotion Agencies (IPAs) to encourage a well-connected business environment. Meanwhile, the Philippines amended the Public Service Act to liberalize various industries to attract more foreign investment. Indonesia updated its Negative Investment List to open up more sectors, particularly in e-commerce, logistics, and tourism.

3. Determinants of FDI

Based on the literature, FDI is an important economic driver for a host country. As such, it is critical to understand the drivers of FDI flows, which host countries may use as basis to develop strategies that encourage or foster foreign direct investments into a host country. It is critical for policymakers, economists, and businesses to understand FDI flows as they study international investment trends, assess the impact on host and home nations, and develop strategies to encourage or engage in FDI.

Diverse factors influence FDI attraction in host countries, varying across regions, countries, and sectors. Per existing literature, economic variables play a crucial role in influencing FDI. Countries with larger populations would have higher potential demand and lower costs due to economies of scale (Resmini, 2000; Bevan and Eastrin, 2000; and Bhavan et al., 2010), while openness to trade and investments, and higher levels of trade indicate a country's positive disposition towards foreign trade. Zaman et al. (2018) found that higher openness to trade, defined as the sum of a country's exports and imports as a share of GDP, positively impacts FDI inflows in India, Iran, and Pakistan, while Resmini (2000) found that manufacturing sectors in Central and Eastern European countries benefit from increased trade openness.

Additionally, weaker exchange rates resulted in an increase in FDIs as relatively lower prices in host countries incentivized foreign firms. Froot and Stein (1991) found that countries with weak currencies tend to have more significant FDI inflows. Contrarily, a stronger real exchange rate increases costs, incentivizing foreign firms to produce domestically.

Institutional and political stability are important factors that investors consider when entering foreign markets. Uddin et al. (2019) found that institutional factors, such as the size of the government, legal structure, strong property rights, freedom to trade, and civil liberty significantly affect FDI inflows in Pakistan, while Schneider and Frey (1985) found that political instability significantly reduces the FDI inflows.

4. Machine learning approaches in analyzing FDI

The increasing volume and complexity of FDI datasets made extracting useful information using traditional analytical processes more challenging. To address this, analysts and researchers are actively exploring ML approaches to uncover hidden correlations and non-linear relationships among various factors influencing investment decisions. For instance, Singh (2023) developed an interpretable machine learning (IML) framework to examine FDI inflow in Europe using the data from the World Bank from 1995 to 2018. In this study, we explored supervised and unsupervised learning methodologies to understand FDI dynamics using data from investing and recipient economies.

4.1 Supervised learning

Supervised learning involves training ML models on historical FDI data where the outcomes are known. The trained models can then generalize patterns from the historical data to make predictions and generate a feature importance list to identify the top determinants of FDI in a given timeframe.

Random Forest

Random Forest (RF) is an ensemble learning method known for building multiple decision trees with random subsets of data and features. It builds multiple decision-making models and then combines their outputs to make more accurate predictions, as shown in Figure 2. RF is robust to overfitting and can handle large datasets with high dimensionality. Several studies used RF, such as Jiménez and Herrero (2019), which explored feature selection for FDI in Spain, and Horobet et al. (2021), which investigated driving factors of business profitability in European high-tech vs. lowtech companies. The former revealed that urbanization, GDP growth rate, and unemployment significantly influence country-level FDI, while the latter indicated that the impact of FDI is more substantial for profitability in higher technologically intensive industries.

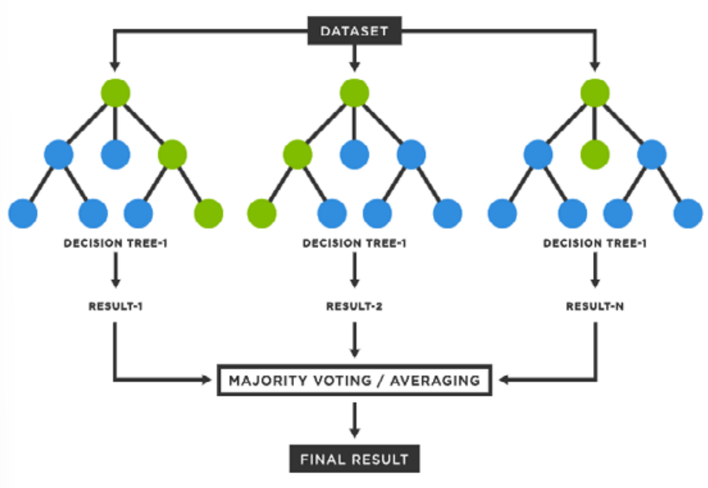

Figure 2. Random Forest

Source: Spotfire.com

Extra Trees Regression

Extra Trees Regression extends the RF algorithm by elevating the randomness further in building the decision trees. Each tree is trained on a random subset of features, and at each split, a random subset of potential splits is considered. This randomness helps reduce overfitting and can result in a more robust and accurate regression model, especially when the dataset has noisy or complex patterns.

Support Vector Regression

Support Vector Regression (SVR) is a regression algorithm based on the concept of Support Vector Machines where the objective is to find a hyperplane that fits the training data within a specified margin called the epsilon-tube (ε-tube), as shown in Figure 3. This minimizes the error of points outside this tube. SVR's performance can be sensitive to the choice of hyperparameters, such as the kernel and regularization parameters. SVR can handle noisy data and outliers, providing more robust predictions and avoiding undue influence from irregularities in the dataset.

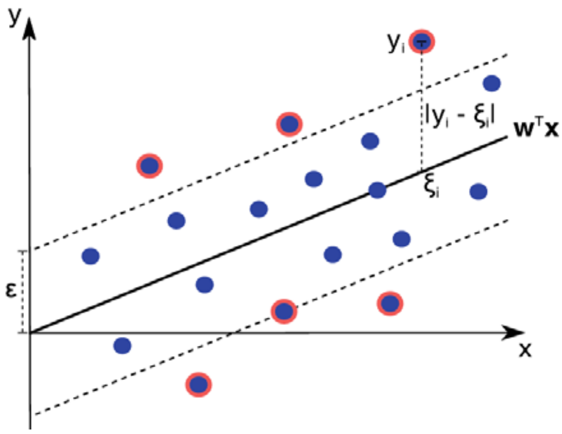

Figure 3. Support Vector Regression

Source: Rosenbaum et al. (2013)

Gradient Boosting Machines

Gradient Boosting Machines build an ensemble of weak learners, refining predictions by minimizing residuals at each step. It excels in capturing complex relationships, providing high predictive accuracy, and is robust to outliers and missing data. Giraldo et al. (2023) utilized extreme gradient boosting (XGBoost) and SHAP Additive Explanations to investigate sovereign risk determinants across countries from 2002 to 2021, while Zhou et al. (2023) identified several macroeconomic factors affecting FDI inflow to China during the pandemic using XGBoost tree regression model – including correlation between the actual monthly data of FDI and the economic variables.

CatBoost Regression

CatBoost is an intelligent algorithm that combines decision trees and gradient boosting to make accurate predictions. Boosting involves combining weaker models to create a robust predictive model. CatBoost grows "oblivious trees," where nodes at the same level test the exact predictor with the same condition. This unique tree-growing approach simplifies the process, thus making it efficient for computation while also preventing overfitting for better predictions.

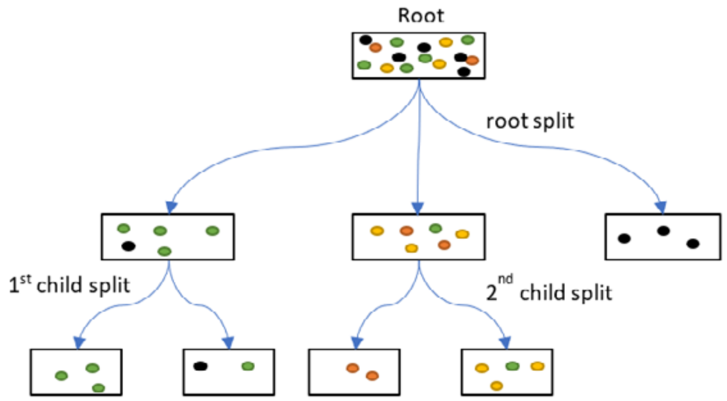

Figure 4. CatBoost Regression

Source: Prokhorenkova et al. (2018)

4.2 Unsupervised learning

As countries integrate into the global economy, the interactions between investing and receiving nations have become increasingly complex. Unsupervised learning techniques, such as association analysis and collaborative filtering, provide a novel lens through which we can discern hidden patterns, correlations, and clusters in the complex FDI dataset.

Association Rule Mining

Association rule mining is a technique used to discover hidden relationships between variables in large datasets. It is a popular method in data mining and machine learning. It has various applications in various fields, such as market basket analysis, customer segmentation, and fraud detection.

Concept	Formula
Support	$\text{sup}(X) = \frac{(X \cup Y)}{N}$
Confidence	$\text{conf}(X \to Y) = \frac{(X \cup Y)}{X}$
Lift	$\text{lift}(X \to Y) = \frac{sup(X \cup Y)}{sup(X) * sup(Y)}$

Sources: Kim et al. (2017), Yaman et al. (2020)

Support pertains to the fraction of investment instances that flow to a specific set of countries. Confidence refers to how often items in country Y are invested in with country X. Lift shows how many more times than expected X and Y were invested together if they were statistically independent. A lift value must be greater than one to indicate independence between X and Y. The greater the values of support, confidence, and lift, the more associated the countries are.

Cluster Analysis using Collaborative Filtering

Collaborative filtering is employed to unravel shared investment strategies among countries focusing on developing Asian economies. Collaborative filtering is a technique that gathers preferences from numerous users to predict the interests of a particular user automatically. By examining the investment patterns of different nations, this analysis aims to identify countries that exhibit similar strategies in their investments within the Asian region. Mathematically, this can be shown as:

$$sim(a,b) = \frac{\sum_{p\in P}(r_{a,p} - \bar{r_a})(r_{b,p} - \bar{r_b})}{\sqrt{\sum_{p\in P}(r_{a,p} - \bar{r_a})^2}\sqrt{\sum_{p\in P}(r_{b,p} - \bar{r_b})^2}}$$

where a and b are investing countries, $r_{a,p}$ is the inflow of an investing country to a recipient country, and P is the set of countries invested in by both countries a and b.

This method analyzes historical investment data in the context of FDI without requiring pre-existing labels or training sets. By utilizing the inherent connections between investors and their investment decisions, collaborative filtering sheds light on obscure trends and provides a sophisticated comprehension of the complex preferences influencing FDI decisions.

5. The Variables and Data

According to Bretas et al. (2021), companies prioritize host markets offering good market conditions (e.g., market growth, size, trade flows, open trade regimes and regional integration), good access and entry conditions, good production conditions (e.g., low cost of production and labor, availability of natural resources), good institutional framework (governance and acceptable risk) and suitable structure for FDI (e.g., financial development, political stability, inflation, exchange and interest rates, taxes and capital regulation).

To study the FDI determinants, we analyzed yearly observations from 2008 to 2022 (15 years) for 20 developing Asian countries. The datasets are obtained from four databases (i.e., the United Nations Conference on Trade and Development's Bilateral FDI Statistics, the International Monetary Fund (IMF) DataMapper Datasets, Word Development Indicators DataBank, and ADB Key Indicators Database). Initially, we gathered 38 economic, institutional, political, and environmental indicators, as listed in Appendix A. However, upon checking the completeness and fit for analysis, these were trimmed down to 18 variables listed in Appendix B.

FDI inflow data per country is presented in Figure 5, which shows that most of the country samples received FDI inflows below 10% of GDP over time, while there are exemptions like Hong Kong, Singapore, and Mongolia that have relatively higher inflows in certain periods. Notably, inflows in Mongolia are distinct in some periods like 2011, when it had its highest inflow at 43% of GDP and its lowest in 2016 at -37%.

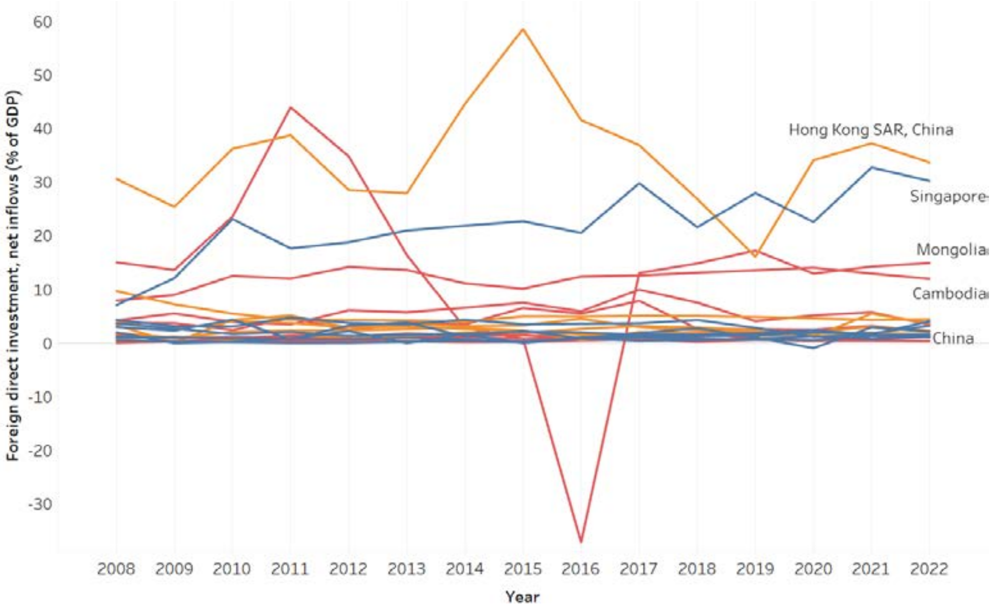

Figure 5. FDI Time Series per Country

Source: World Development Indicators Databank

As shown in Figure 6, the relationship among variables is explored using correlation coefficient analysis. We note that some variables, like GDP per capita and government efficiency, correlate highly with other institutional/political variables. To avoid multicollinearity, 'GDP_CAP_CURR', 'GOVT_EFF', 'RULE_LAW', 'CORRUPT_CONTROL', and 'REG_QUAL' were disregarded in the analysis.

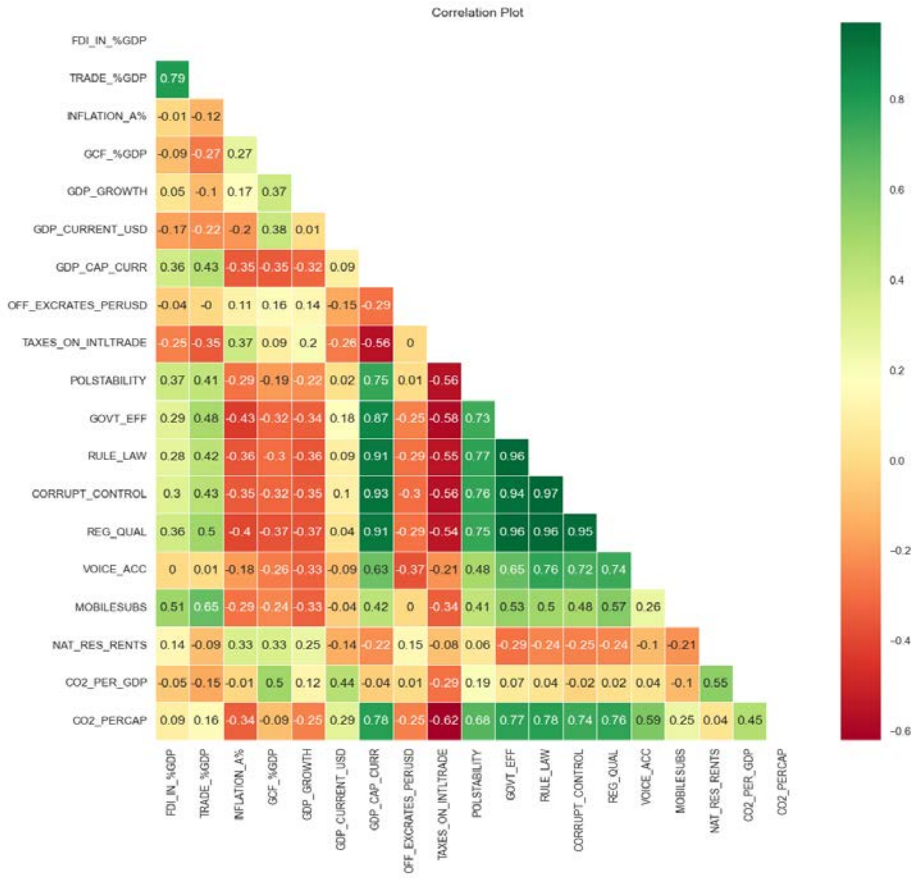

Figure 6. Correlation Heatmap of Variables

Source: Authors' computation

For the unsupervised learning methods, the FDI data was gathered from the IMF's Coordinated Direct Investment Survey (CDIS). This voluntary data collection exercise assembles data on countries' direct investment positions to build a database on from-whom-to-who cross-border direct investment positions and advance knowledge of financial interconnection.

6. Key Observations/Results

This section presents and discusses results from applying ML techniques to answer the questions formulated in the previous sections.

6.1 Supervised learning

As seen in Figure 7, trade openness is highly correlated with the FDI net inflows. The positive relationship between trade openness and FDI underscores the importance of a conducive trade environment. Non-resident investors are more likely to establish operations in a host country when they can easily sell and move their goods and services around the world. This necessitates fewer import and export restrictions, such as tariffs, quotas, and licensing requirements, which enhance market access and reduce trade barriers. As a result, a more open trade policy fosters an environment that attracts FDI by providing opportunities for international trade and investment. This agrees with the majority of empirical studies that found a positive relationship between trade openness and FDI inflows, such as Makoni (2018), Sahoo (2006), Janick and Wunnava (2004), and Zaman et al. (2018). The positive relationship between trade openness and FDI indicates that fewer import and export restrictions better attract FDI.

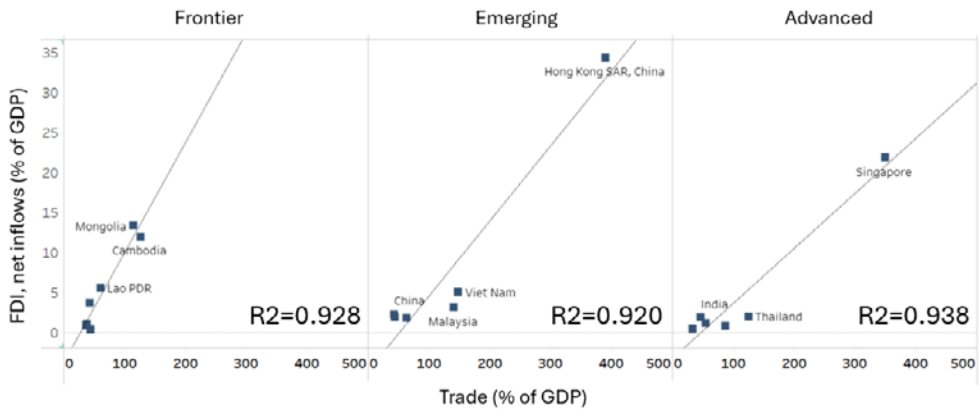

Figure 7. Trade openness vs. Average FDI net inflows

Source: Authors' computation

Apart from trade openness, the importance of other factors was explored using different ML approaches. Unlike cross-country studies by Sattarov (2012), O'Meara (2015), Jahan and Paul (2021), and Bénétrix et al. (2023) that examined relationships between FDI and other macroeconomic factors using econometric models that have an R-squared ranging from 0.40 to 0.61, the models created for this study resulted in R-squared of 0.54 to 0.81 by using various ML models to analyze all country sample. Table 2 summarizes the model performances of five ML models. Different models worked best for different samples: Extra Trees Regressor is effective in generalizing the overall trends of FDI inflows, while Random Forest, Support Vector, and CatBoost regressions are best for specific country groups, suggesting that the fit of ML models depends on the datasets used.

Evaluation Metrics

Table 2

	All Samples	Frontier	Emerging	Advanced
Extra Trees Regression				
R squared	**0.807****	0.207	0.386	0.839
Normalized RMSE*	**4.257**	4.068	0.967	4.310
MAPE	**0.618**	1.395	0.791	1.785
Random Forest				
R squared	0.736	**0.724****	0.319	0.878
Normalized RMSE*	4.818	**3.513**	1.057	3.965
MAPE	1.173	**1.695**	0.863	0.837

Evaluation Metrics

Table 2

	All Samples	Frontier	Emerging	Advanced
Gradient Boosting Method				
R squared	0.752	0.543	0.361	0.842
Normalized RMSE*	4.453	4.050	0.995	4.617
MAPE	0.933	1.602	0.667	1.695
Support Vector Regression				
R squared	0.541	0.286	**0.513****	0.679
Normalized RMSE*	6.594	5.119	**1.033**	6.192
MAPE	1.341	3.477	**0.801**	1.289
CatBoost Regression (Decision Tree + Gradient Boosting)				
R squared	0.767	0.614	0.436	**0.910****
Normalized RMSE*	4.570	3.805	0.955	**3.784**
MAPE	0.635	1.917	0.8035	**0.821**

* normalized by the standard deviation.
** best model (tuned)
Sources: Alon et al. (2022), Faruq (2023), Kurul (2017), Phung (2017)

The best-performing model, i.e., Extra Trees Regressor, was used to get the top features. Table 3 provides the importance or weights of the top variables used to predict FDI inflows. The most important determinant is trade openness for all samples, which can explain 47% of the variance in the dataset. However, this is not the case in emerging countries as this may suggest the data sparsity in this country group.

Other variables deemed crucial in predicting the FDI inflows include carbon intensity, total natural resource rents, gross capital formation (GCF), exchange rate, and institutional factors like political stability, and voice and accountability.[3] The exchange rates and GCF prove to be crucial determinants. The results support the findings of Alba et al. (2010), Suliman et al. (2015), and Tan et al. (2021) that exchange rates and FDIs are inversely related. This phenomenon stems from the notion that weaker exchange rates attract FDIs because input prices are comparatively more affordable. Likewise, a high GCF, representing the total value of capital goods produced in an economy, reflects the country's commitment to infrastructure development and capacity building, signaling a favorable environment for foreign investors.

[3] Refer to Appendix B for the complete definition of these variables.

Feature Importance

Table 3

Variable	All Samples	Frontier	Emerging	Advanced
Economic				
Trade openness	**0.469**	**0.297**	0.080	**0.560**
Inflation/macroeconomic factors		0.060	0.059	
Gross capital formation	0.056	**0.142**	0.059	
GDP growth rate			0.075	
Exchange rate	0.063	0.074	**0.270**	
Institutional/Political				
Political stability		0.050	**0.111**	
Voice and accountability			**0.083**	**0.096**
Infrastructure				
Infrastructure capability	0.059		0.062	
Environmental				
Total natural resource rents	**0.086**	**0.084**	0.052	
Carbon Intensity	**0.070**	0.052		**0.117**

Note: The top 3 features are highlighted.

Consistent with Rashid et al. (2017), Sabir et al. (2019), and Kinuthia and Murshed (2015), the results show that institutional factors, such as political stability and voice and accountability, especially in emerging economies, are crucial in attracting FDI due to the confidence they instill in investors regarding the protection of their investments and the conducive business environment. Political stability reduces the risk associated with abrupt policy changes, government upheavals, and social unrest, which creates a more predictable and secure atmosphere for foreign investments. Further, voice and accountability, which captures perceptions of citizens' freedom to select their government, freedom of expression and association, and free press, is associated with better protection of property rights, lower corruption levels, and stronger institutions, which are factors that appeal to international investors seeking a stable and reliable investment environment.

While few studies accounted for carbon intensity and total natural resource rents as FDI inflow determinants, the results show that these factors highly contribute to the attractiveness of a host country to foreign investors. Natural resource rents are the surplus profits from utilizing natural resources. This act as an incentive for FDI as they represent an opportunity for investors to tap into exclusive resources available in recipient countries. Additionally, the significance of carbon intensity in determining FDI inflows shows how investors are becoming more attuned to the environmental impacts of their operations, and regions with lower carbon intensity are perceived as more sustainable and less exposed to future regulatory risks associated with climate change. This aligns with global movements towards achieving carbon neutrality and mitigating climate change, as highlighted in international environmental agreements.

6.2 Unsupervised learning

Using exploratory data analysis and unsupervised techniques, we uncovered the similarities between investing countries. Figure 8 shows that most of the investments flowing to developing Asian countries come from either the Hong Kong Special Administrative Region (SAR) or the United States. However, looking further into each country group, different investing nations are observed to lead the investment patterns: Thailand and South Korea in the frontier (Figure 9), Hong Kong SAR in emerging (Figure 10), and the United States in the advanced ones (Figure 11). This shows the differing investment preferences of top investing countries in the region.

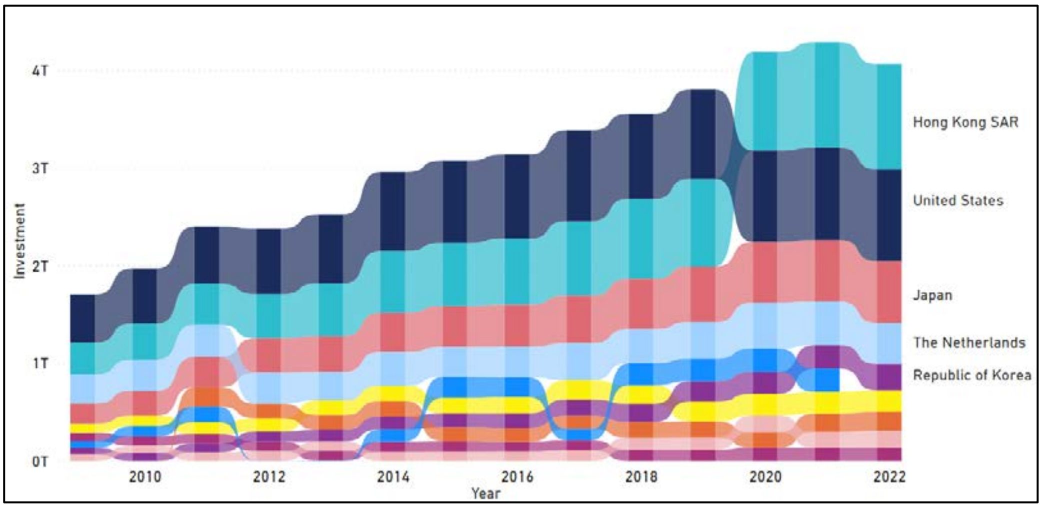

Figure 8. Outward Position of Investing Countries in Developing Asia, 2009 to 2022 (US Dollars)

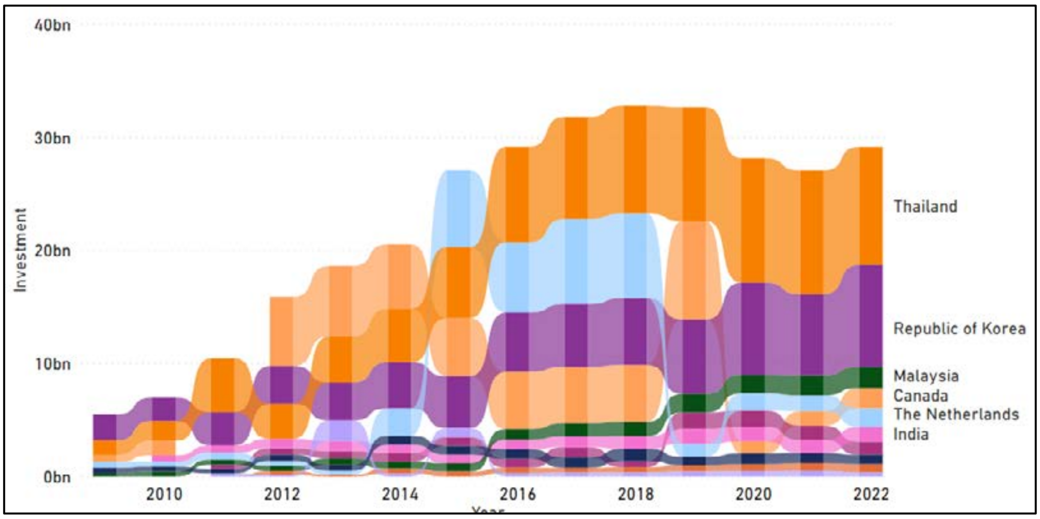

Figure 9. Outward Position of Investing Countries in Frontier Countries, 2009 to 2022 (US Dollars)

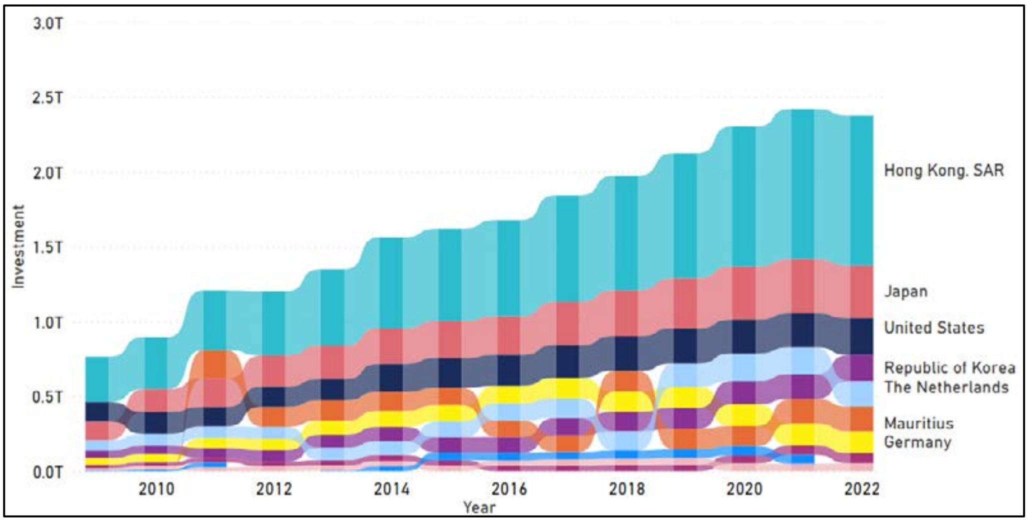

Figure 10. Outward Position of Investing Countries in Emerging Countries, 2009 to 2022 (US Dollars)

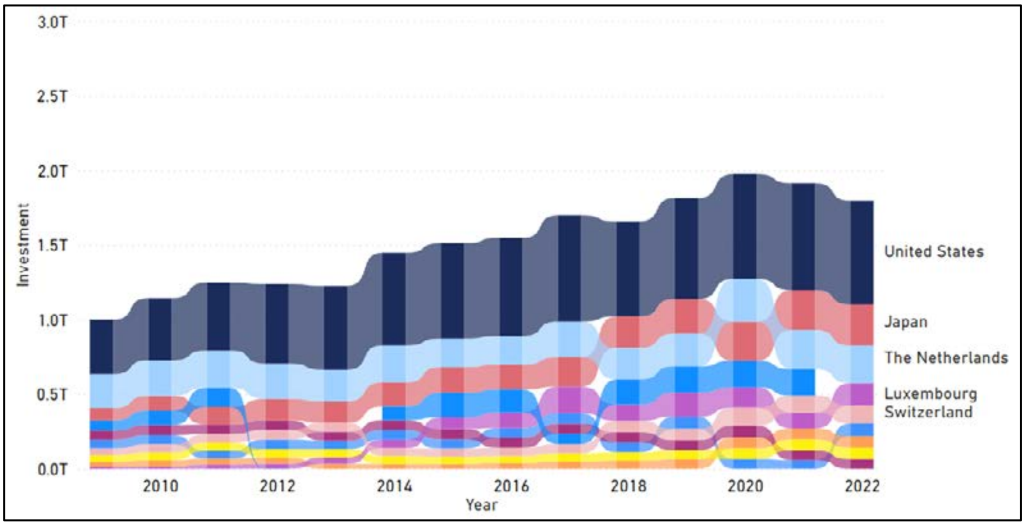

Figure 11. Outward Position of Investing Countries in Advanced Countries, 2009 to 2022 (US Dollars)

In Table 4, the results from association mining show the frequently invested pairs or clusters that are often chosen together as FDI recipients. Investing nations are observed to be co-investing in Hong Kong SAR, Singapore, India, and China. Because of their strategic locations, Hong Kong SAR and Singapore are major worldwide financial and trade hubs. They act as entry points to Asia and allow trade between the East and West. Meanwhile, China and India have diverse economies and large domestic markets. China is recognized as the "World's Factory" by housing 28% of the world's manufacturing, while India is a significant participant in IT services, pharmaceuticals, and other industries.

Regarding trade volume, China is a major worldwide exporter and importer. It maintains extensive trading links with countries all around the world. Hong Kong SAR and Singapore are known for their high trade volumes. They serve as major trading hubs with extensive shipping and logistics networks. The identified most co-invested recipient countries are highly open economies with minimal trade barriers, low taxation, and well-developed infrastructure. They also actively participate in various multilateral trade agreements (e.g., the South Asian Free Trade Area and the Regional Comprehensive Economic Partnership).

Furthermore, this is In line with the observations of Le Leslé et al. (2014) that Hong Kong SAR's and Singapore's economy and trade will become more interconnected in the future and that financial system stability will be enhanced if both countries act in a complementary fashion. This further suggests that both countries are stepping up outreach efforts to raise their profile among the international community.

Results of Association Analysis

Table 4

Antecedents	Consequents	Support	Confidence	Lift
Hong Kong SAR	Singapore	0.4619	0.8729	1.6075
Singapore	Hong Kong SAR	0.4619	0.8506	1.6075
India	Singapore	0.4570	0.8416	1.5500
Singapore	India	0.4570	0.8416	1.5500
Hong Kong SAR	China	0.4910	0.9279	1.5257
China	Hong Kong SAR	0.4910	0.8073	1.5257
Singapore	China	0.5000	0.9208	1.5140
China	Singapore	0.5000	0.8221	1.5140
China	India	0.4695	0.7959	1.4657

Source: Authors' computation

The results from collaborative filtering suggest that Switzerland, France, Canada, Japan, Denmark, Australia, and the Netherlands share common investment patterns in Asian economies, as illustrated in Figure 12 and detailed in Annex C. To understand the investor preferences of firms in these countries, we examined the specific countries within Asia where these firms choose to expand their business operations.

Figure 12. Collaborative Filtering Results
Note: The edges or links are based on the similarity scores, while the nodes or vertices denote the degree or the number of similar countries.

These investing countries are at the forefront of technological advancements and innovations. Their investment in host countries like Hong Kong SAR, Singapore, India, and China, as detailed in Table 5, may include technology, research, infrastructure development, manufacturing, and even renewable energy. Similar economic strategies, common investment interests, political and regulatory alignment, and even cultural and historical factors may also play a role. Further research into these areas of interest will be worthwhile in the future.

Top Five Asian Investment Destinations from Switzerland, France, Canada, Japan, Denmark, Australia, and the Netherlands in 2022

Table 5

Country	FDI Inflows
Singapore	351,834.28
Mainland China	277,415.98
India	107,488.01
Hong Kong SAR, China	95,143.74
Thailand	93,962.27

Source: Authors' computation based on the CDIS

We noted that the specific sectors and industries targeted for investment can vary depending on the investing and receiving countries' economic strengths and requirements. Furthermore, geopolitical issues, regulatory frameworks, and cultural variables are essential in defining investment strategy.

7. Conclusion and Recommendations

This study explored different ML techniques to examine the FDI determinants in developing Asian nations using the latest economic, political, institutional, and environmental indicators from several open-source platforms of international organizations. Extra Trees Regressor has the highest coefficient of determination at 0.807 in identifying the top features of all developing Asian nations. In contrast, CatBoost Regression has an R-squared of 0.910 for data on advanced Asian countries. These numbers mean that the features selected by the Extra Trees and CatBoost Regressors collectively account for a significant portion (i.e., 80.7% and 91%) of the variability observed in the development-related metric for the developing Asian nations and Advanced ones, respectively. These supervised ML models perform better than previous relevant studies using econometric models with R-squared ranging from 0.40 to 0.61. This indicates that ML models can effectively identify and analyze the key determinants of FDI and, hence, can be further leveraged to improve and supplement current traditional models to explore complex datasets like those of international trade.

The analysis of FDI determinants in developing Asia reveals several key factors influencing FDI inflows, including trade openness, GCF, exchange rate dynamics, political stability, voice and accountability metrics, total natural resource rents, and carbon intensity. Notably, the significance of these determinants varies across country classifications. In frontier countries, FDI is closely associated with trade openness, GCF, and natural resource rents. These economies often prioritize policies that facilitate international trade and investment while requiring substantial investments in infrastructure, technology, and human capital to support economic development. Total natural resource rents represent a valuable asset for many frontier countries. Rich endowments of natural resources, such as minerals, oil, or agricultural land, can attract significant FDI inflows from multinational corporations seeking to extract these resources. In emerging countries, Governments often implement policies to maintain exchange rate stability, such as adopting flexible exchange rate regimes or intervening in currency markets when necessary, to instill confidence among foreign investors. Also, emerging countries with stable political environments are perceived as safer and more conducive to long-term investment, as they offer predictability and security for businesses.

Conversely, advanced countries exhibit a pronounced relationship between FDI and trade openness, voice and accountability measures, and carbon intensity considerations. Advanced countries often prioritize trade agreements and integration initiatives to enhance their attractiveness to foreign investors further. These countries are found to have transparent and accountable governance structures, as they provide assurance of stability, predictability, and legal protection for investments. Also, with growing awareness of environmental sustainability and climate change concerns, advanced countries are transitioning towards low-carbon and sustainable development pathways. These findings underscore the nuanced nature of FDI determinants, contingent upon the respective countries' developmental stage and economic characteristics. These findings on economic and institutional determinants are consistent with the literature, such as the studies of Rashid et al. (2017), Sabir et al. (2019), and Tan et al. (2021).

Interestingly, the ML model identified environmental variables like the total natural resource rents and carbon intensity as significant FDI determinants. To date, few studies have accounted for these environmental variables. This may be a call for policymakers in developing Asian nations to undertake reforms such as promoting the adoption of green technology and practices, shifting towards cleaner and renewable energy resources, establishing clear and consistent carbon pricing policies, and establishing financial mechanisms, like green bonds, to support the transition of industries heavily reliant on natural resources.

Using association analysis, we found that investing nations mostly co-invest in Hong Kong SAR and Singapore. This is in line with the observations of an IMF study done by Le Leslé et al. (2014), identifying these countries as Asia's preeminent international finance centers. Hong Kong SAR and Singapore are found to have complementary evolution paths, each tending to specialize in different asset markets and financial services, focusing on different parts of Asia. Given the consistent concentration of co-investment in these countries, competition within Hong Kong SAR and Singapore might intensify. While this could pose challenges, it could also drive increased market efficiency and innovation in each country, and other developing Asian countries can learn from their experience.

Results from collaborative filtering suggest shared investment patterns among Switzerland, France, Canada, Japan, Denmark, Australia, and the Netherlands. The algorithm identified the commonalities in their investment behaviors, particularly in Asian economies. Given this, recipient countries can analyze the sectors and types of projects that attract investments from the identified countries. This insight can help them align their economic development plans with the preferences of these investors. The innovation and technology-related opportunities driving these collaborative investments may be explored to guide efforts in fostering innovation ecosystems to attract FDIs from multiple countries. Recipient countries can further assess whether the collaborative investments are concentrated in specific regions or span different parts of the world. This information can guide regional economic development strategies and partnership initiatives.

This study highlights the potential for leveraging ML techniques to enhance our understanding of FDI dynamics. While supervised ML models show promise in predicting FDI levels accurately, there is a notable gap in utilizing unsupervised ML techniques. Exploring clustering algorithms like K-means can illuminate patterns in FDI behavior across countries or sectors, informing targeted policy interventions. Additionally, employing association rule mining techniques can reveal co-investment patterns, aiding policymakers in optimizing resource allocation. Furthermore, incorporating labor data into the analysis can provide valuable insights into the labor market's role in shaping FDI decisions, thereby improving predictive accuracy and informing evidence-based policymaking.

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Appendix A

Original Set of Variables

Type	Variable
Economic	Business extent of disclosure index (0=less disclosure to 10=more disclosure)
Economic	CPIA business regulatory environment rating (1=low to 6=high)
Economic	Cost to export, border compliance (US$)
Economic	Cost to export, documentary compliance (US$)
Economic	Cost to import, border compliance (US$)
Economic	Cost to import, documentary compliance (US$)
Economic	Exports of goods and services (% of GDP)
Economic	Foreign direct investment, net (BoP, current US$)
Economic	Foreign direct investment, net inflows (% of GDP)
Economic	Foreign direct investment, net outflows (% of GDP)
Economic	GDP (current US$)
Economic	GDP growth (annual %)
Economic	GDP per capita (current US$)
Economic	Government Effectiveness: Estimate
Economic	Gross capital formation (% of GDP)
Economic	Imports of goods and services (% of GDP)
Economic	Inflation, consumer prices (annual %)
Economic	Lending interest rate (%)
Economic	Logistics performance index: Quality of trade and transport-related infrastructure (1=ow to 5=high)
Economic	Real effective exchange rate index (2010 = 100
Economic	Real interest rate (%)
Economic	Taxes on international trade (% of revenue)
Economic	Trade (% of GDP)
Economic	Official Exchange Rates (local currency units per $, period averages), National Currency Unit per US Dollar
Environmental	Total natural resources rents (% of GDP)
Environmental	PM2.5 air pollution, population exposed to levels exceeding WHO guideline value (% of total)
Environmental	Carbon Intensity (kg of CO2, equivalent per constant 2017 $)
Environmental	CO2 emissions (metric tons per capita)
Environmental	Adjusted savings: carbon dioxide damage (% of GNI)
Environmental	Adjusted savings: carbon dioxide damage (current US$)
Environmental	Natural gas rents (% of GDP)
Infrastructure	Electricity production from oil, gas, and coal sources (% of total)
Infrastructure	Mobile cellular subscriptions (per 100 people)
Institutional/Political	Control of Corruption: Estimate

Institutional/Political	Political Stability and Absence of Violence/Terrorism: Estimate
Institutional/Political	Regulatory Quality: Estimate
Institutional/Political	Rule of Law: Estimate
Institutional/Political	Voice and Accountability: Estimate

Sources: TableNote

Appendix B

List of variables used in the ML models

Variable	Description	VarName
Dependent/Target		
Foreign Direct Investment	FDI, net inflows (% of GDP)	FDI_IN_%GDP
Independent		
Economic		
Trade openness	The sum of imports and exports (% of GDP)	TRADE_%GDP
Inflation/macroeconomic factors	Inflation, consumer prices (annual %)	INFLATION_A%
Gross capital formation	Indicates the savings of the country (% of GDP)	GCF_%GDP
GDP growth rate	The annual average rate of change of the GDP at market prices based on constant local currency, for a given national economy, during a specified period. (%)	GDP_GROWTH
Nominal GDP	The total value of all goods and services produced in a given year. (USD)	GDP_CURRENT_USD
GDP per capita	GDP per capita in current terms. (USD)	GDP_CAP_CURR
Exchange rate	The real effective exchange rate, base 2010 (%)	OFF_EXCRATES_PERUSD
Taxes on international trade	Taxes on international trade include import duties, export duties, profits of export or import monopolies, exchange profits, and exchange taxes. (% of revenue)	TAXES_ON_INTLTRADE
Institutional/Political		
Political stability (-2.5=Low to 2.5=High)	Measure perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism.	POLSTABILITY
Government effectiveness (-2.5=Low to 2.5=High)	Capture perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	GOVT_EFF
Rule of Law (-2.5=Low to 2.5=High)	Captures perceptions on rules of society, quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	RULE_LAW
Control of corruption (-2.5=Low to 2.5=High)	Captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	CORRUPT_CONTROL
Regulatory quality (-2.5=Low to 2.5=High)	Captures perceptions of the ability of the government to formulate and implement sound	REG_QUAL

		policies and regulations that permit and promote private sector development.	
	Voice and accountability (-2.5=Low to 2.5=High)	Captures perceptions of the extent to which a country's citizens can participate in selecting their government, as well as freedom of expression, freedom of association, and a free press.	VOICE_ACC
Infrastructure			
	Infrastructure capability[1]	Mobile cellular subscriptions (per 100 people)	MOBILESUBS
Environmental			
	Total natural resource rents	The sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. (% of GDP)	NAT_RES_RENTS
	Carbon Intensity	Captures the amount of carbon dioxide (CO2) emissions produced per unit of GDP. (kg of CO_2 equivalent per constant USD 2017)	CO2_PER_GDP
	CO2 emissions per capita	Captures the contribution of the average citizen of each country by dividing its total emissions by its population. (current USD)	CO2_PERCAP

[1] Proxy variable given the lack of data.

Sources: Alon et. al. (2022), Faruq (2023), Kurul (2017), Phung (2017)

Appendix C

Collaborative Filtering Results

Investor 1	Investor 2	Similarities
Canada	France	0.9661
Denmark	France	0.9661
France	Switzerland	0.9661
France	Japan	0.9636
Australia	France	0.9636
Italy	Republic of Korea	0.9500
The Netherlands	United States	0.9459
The Netherlands	Switzerland	0.9393
Germany	The Netherlands	0.9393
Canada	The Netherlands	0.9393
Germany	Switzerland	0.9333
Canada	Denmark	0.9333
Canada	Switzerland	0.9333
Denmark	Switzerland	0.9333
Japan	Switzerland	0.9309
Australia	Canada	0.9309
Australia	Denmark	0.9309
Canada	Japan	0.9309
Australia	Switzerland	0.9309
Denmark	Japan	0.9309
Australia	France	0.9258
Italy	United States	0.9234
Republic of Korea	Unites States	0.9234

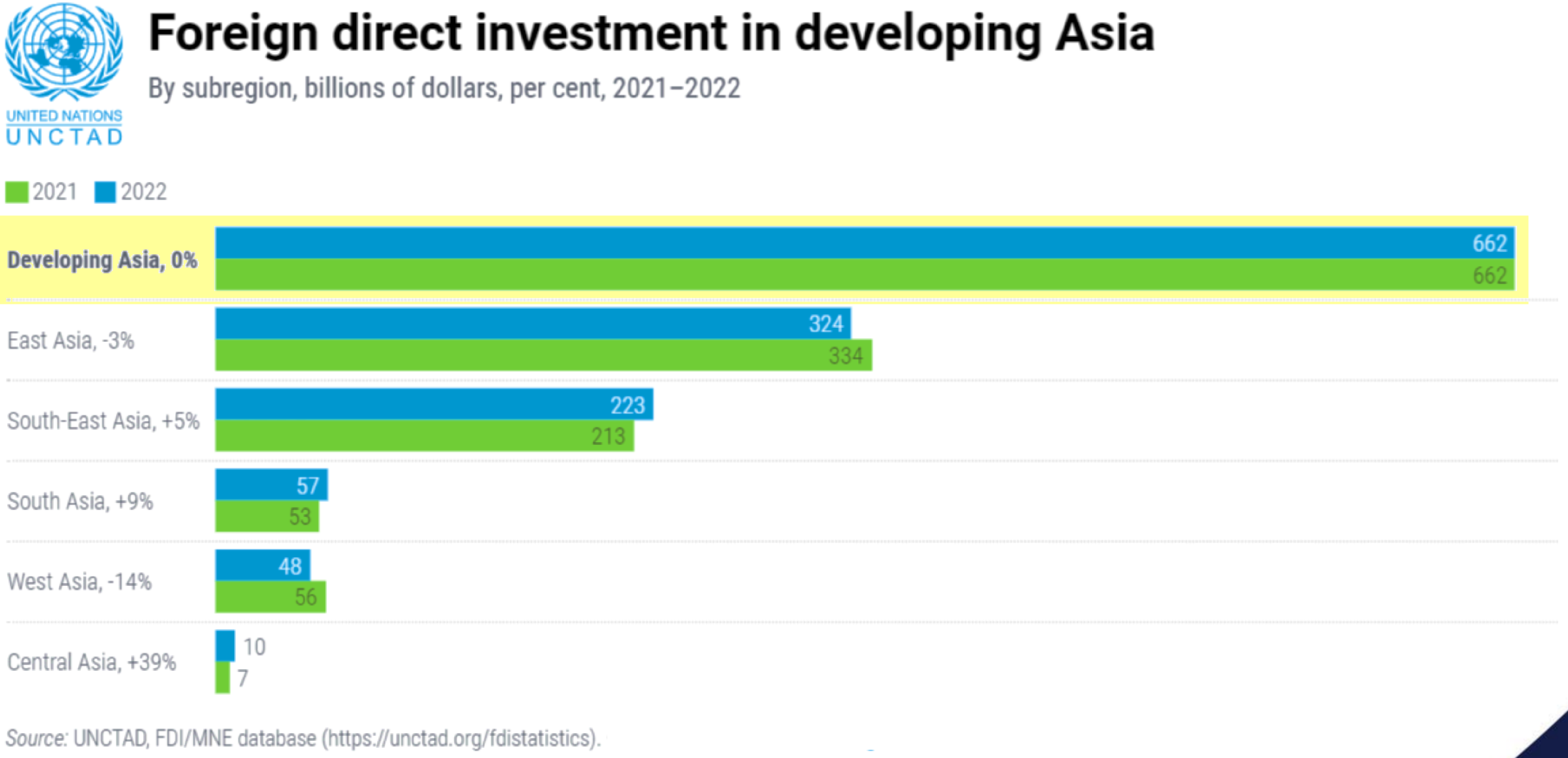
Sources: Authors' computation

Exploring the Evolving Determinants of Foreign Direct Investment and the Investing Country Preferences in Developing Asian Economies using Machine Learning

Carmelita G. Esclanda-Lo
Gabriel A. Masangkay
Chelsea Anne S. Ong
Rossvern S. Reyes

BACKGROUND

Asia received 51% of global inflows but remained steady at USD 662 billion



BACKGROUND

Foreign Direct Investment (FDI) plays a crucial role in the economic development of countries, especially in developing nations.

Benefits of FDI includes:

- Capital Inflow and Economic Growth
- Technology Transfer
- Access to Global Markets
- Infrastructure Development

BACKGROUND

FDI inflows into developing Asian Economies have increased since 1970s

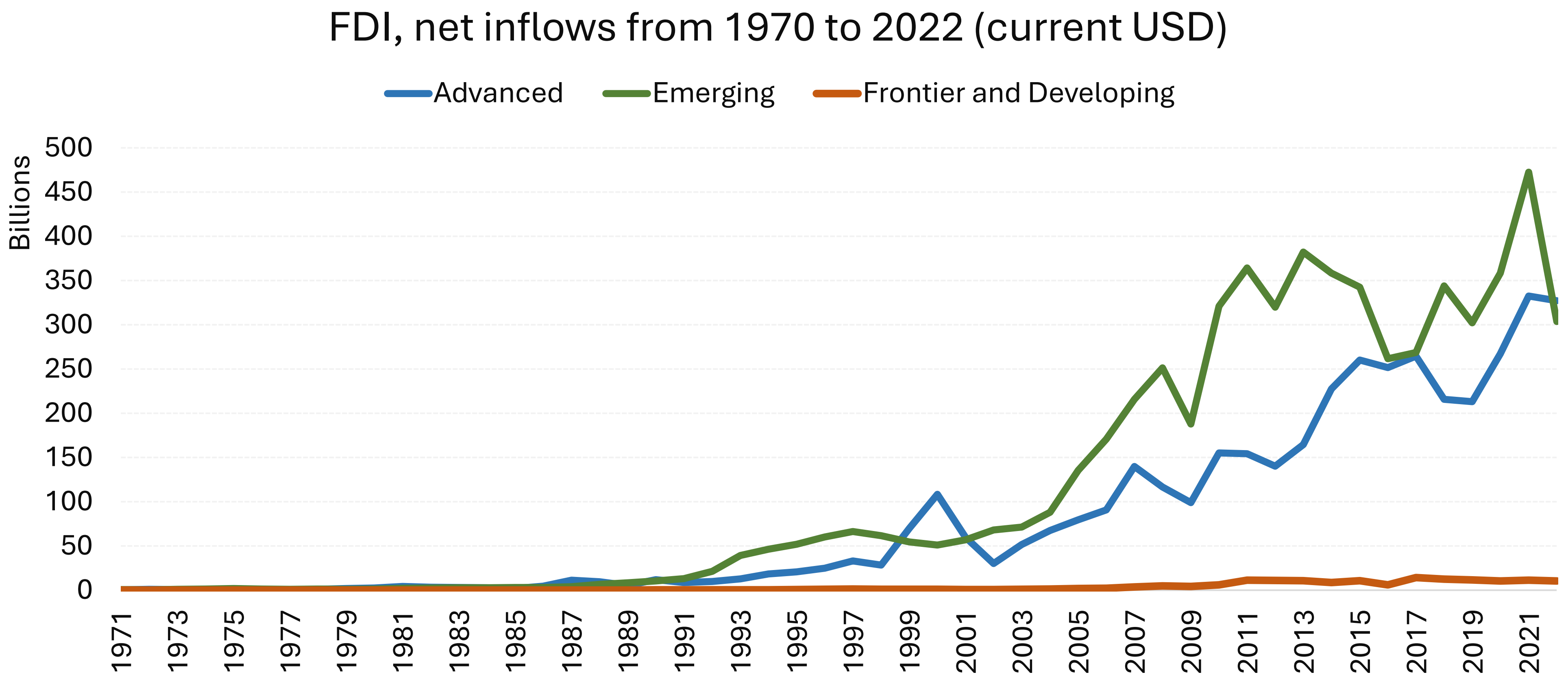


Figure 1. Sum of FDI net inflows (BoP, current USD)
Source: Authors' computation based on the World Development Indicators.

RELATED LITERATURE

Africa:

- Asiedu (2002), Sattarov (2012), Makoni (2018)

Europe:

- Resmini (2000), Bevan and Estrin (2000)

Asia:

- Brooks et al. (2003), Sahoo (2006), Zaman et al. (2018), Bhavan et al. (2010)

OBJECTIVES

1. Utilize ML methods to find non-linear correlations between FDI and its determinants.
2. Use ML methods to analyze feature importance of FDI determinants.
3. Use unsupervised similarity calculations to uncover similarities of comparable investment destinations and investment patterns of foreign investors.

METHODOLOGY

Supervised ML

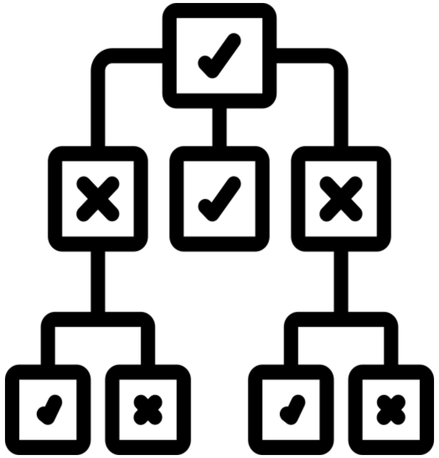
- Random Forest Regression
- Extra Trees Regression
- Gradient Boosting Machines
- CatBoost Regression
- Support Vector Regression

Unsupervised ML

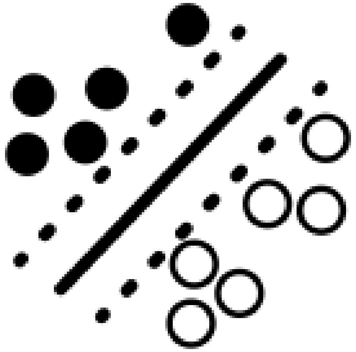
- Association Rule Mining
- Collaborative Filtering

METHODOLOGY

SUPERVISED LEARNING



Random Forest, ExtraTrees, GBM, and CatBoost are variations of a non-linear model that partition the feature space into regions, making decisions based on the values of the features.

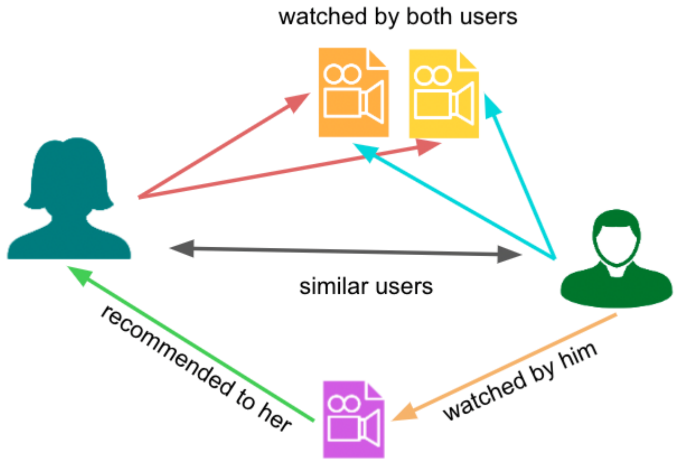


SVM handles non-linear decision boundaries by using kernel functions that implicitly map the input features into a higher-dimensional space where the data may be more separable, allowing for more complex decision boundaries.

METHODOLOGY

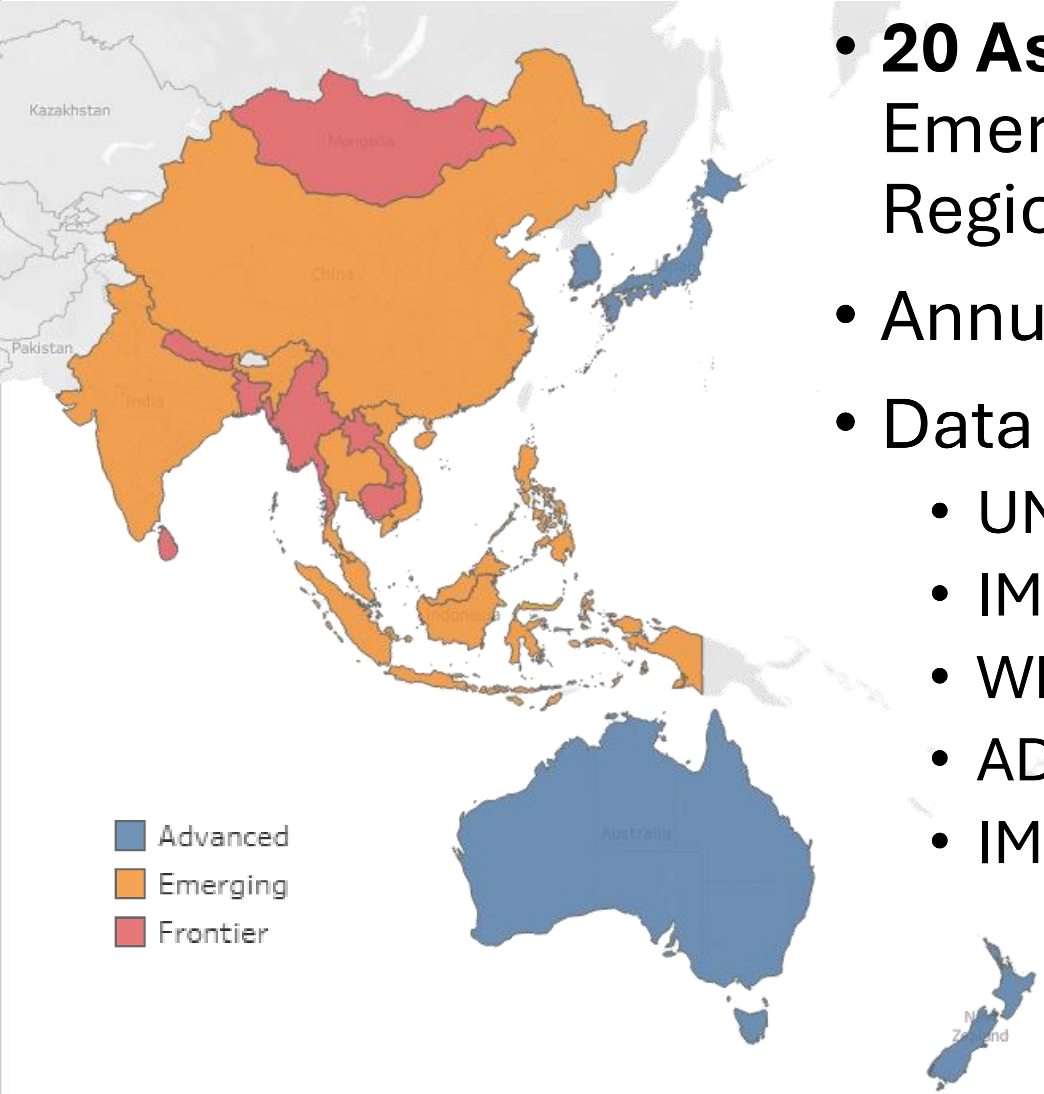
UNSUPERVISED LEARNING

Association rule mining is a data mining technique used to discover interesting relationships or patterns within large datasets. It is commonly applied in market basket analysis to identify frequently co-occurring items in transactions.



Collaborative filtering is a recommendation technique commonly used to identify similarities between users based on their interactions or preferences.

DATA



- **20 Asian countries**, categorized into Advanced, Emerging, and Frontier, as classified in the IMF's Regional Economic Outlook.
- Annual observations from **2008 to 2022**.
- Data sources:
  - UNCTAD Bilateral FDI Statistics,
  - IMF DataMapper Datasets,
  - WB World Development Indicators,
  - ADB Key Indicators Database
  - IMF's Coordinated Direct Investment Survey (CDIS)

DATA

Type	Variable
Dependent/Target	Foreign Direct Investment
Economic	Trade openness
	Inflation/macroeconomic factors
	Gross capital formation
	GDP growth rate
	Nominal GDP
	GDP per Capita
	Exchange rate
	Taxes on international trade
Political	Political stability
	Government effectiveness
	Rule of Law

Type	Variable
Political	Control of corruption
	Regulatory quality
	Voice and accountability
	Political stability
Infrastructural	Infrastructure capability *(Mobile cellular subscriptions (per 100 people))*
	Total natural resource rents
Environmental	Carbon Intensity
	CO2 emissions per capita
	Total natural resource rents

RESULTS

Evaluation Metrics

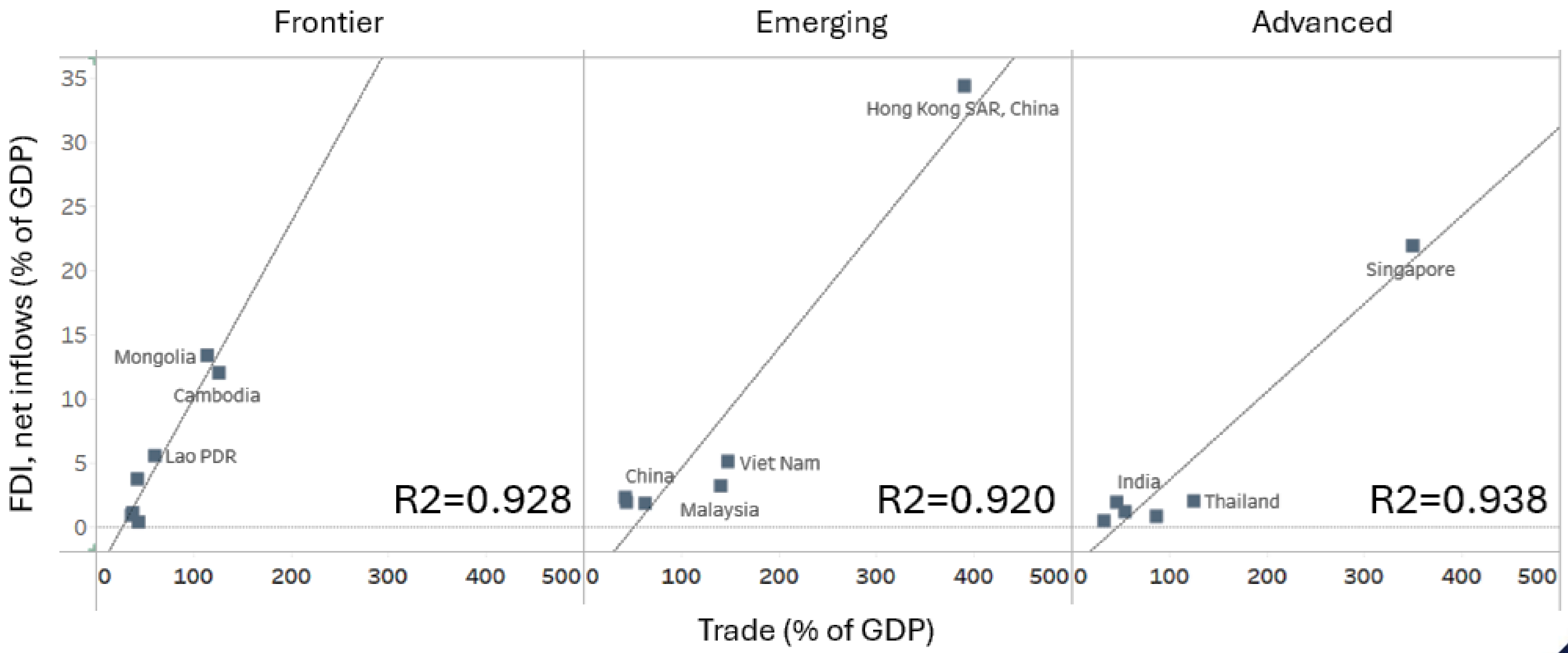
Method	All Samples	Frontier	Emerging	Advanced
Extra Trees Regression				
R squared	**0.807****	0.207	0.386	0.839
Normalized RMSE*	**4.257**	4.068	0.967	4.310
MAPE	**0.618**	1.395	0.791	1.785
Random Forest				
R squared	0.736	**0.724****	0.319	0.878
Normalized RMSE*	4.818	**3.513**	1.057	3.965
MAPE	1.173	**1.695**	0.863	0.837
Gradient Boosting Method				
R squared	0.752	0.543	0.361	0.842
Normalized RMSE*	4.453	4.050	0.995	4.617
MAPE	0.933	1.602	0.667	1.695
Support Vector Regression				
R squared	0.541	0.286	**0.513****	0.679
Normalized RMSE*	6.594	5.119	**1.033**	6.192
MAPE	1.341	3.477	**0.801**	1.289
CatBoost Regression (Decision Tree + Gradient Boosting)				
R squared	0.767	0.614	0.436	**0.910****
Normalized RMSE*	4.570	3.805	0.955	**3.784**
MAPE	0.635	1.917	0.8035	**0.821**

* normalized by the standard deviation.
** best model (tuned)

RESULTS

Trade openness is highly correlated with FDI net inflows.

Figure 7. Trade openness vs. Average FDI net inflows



RESULTS

The study aligns with prior research and establishes Carbon Intensity as a significant predictor of FDI.

Feature Importance

Variable	All Samples	Frontier	Emerging	Advanced
Economic				
Trade openness (++)	**0.469**	**0.297**	0.080	**0.560**
Inflation/macroeconomic factors (+)		0.060	0.059	
Gross capital formation (+)	0.056	**0.142**	0.059	
GDP growth rate (+)			0.075	
Exchange rate	0.063	0.074	**0.270**	
Institutional/Political				
Political stability (+)		0.050	**0.111**	
Voice and accountability (+)			**0.083**	**0.096**
Infrastructure				
Infrastructure capability (++)	0.059		0.062	
Environmental				
Total natural resource rents (+)	**0.086**	**0.084**	0.052	
Carbon Intensity (-)	**0.070**	0.052		**0.117**

RESULTS

The ultimate investors in developing Asia are Hong Kong SAR and the United States, along with Japan and the Netherlands.

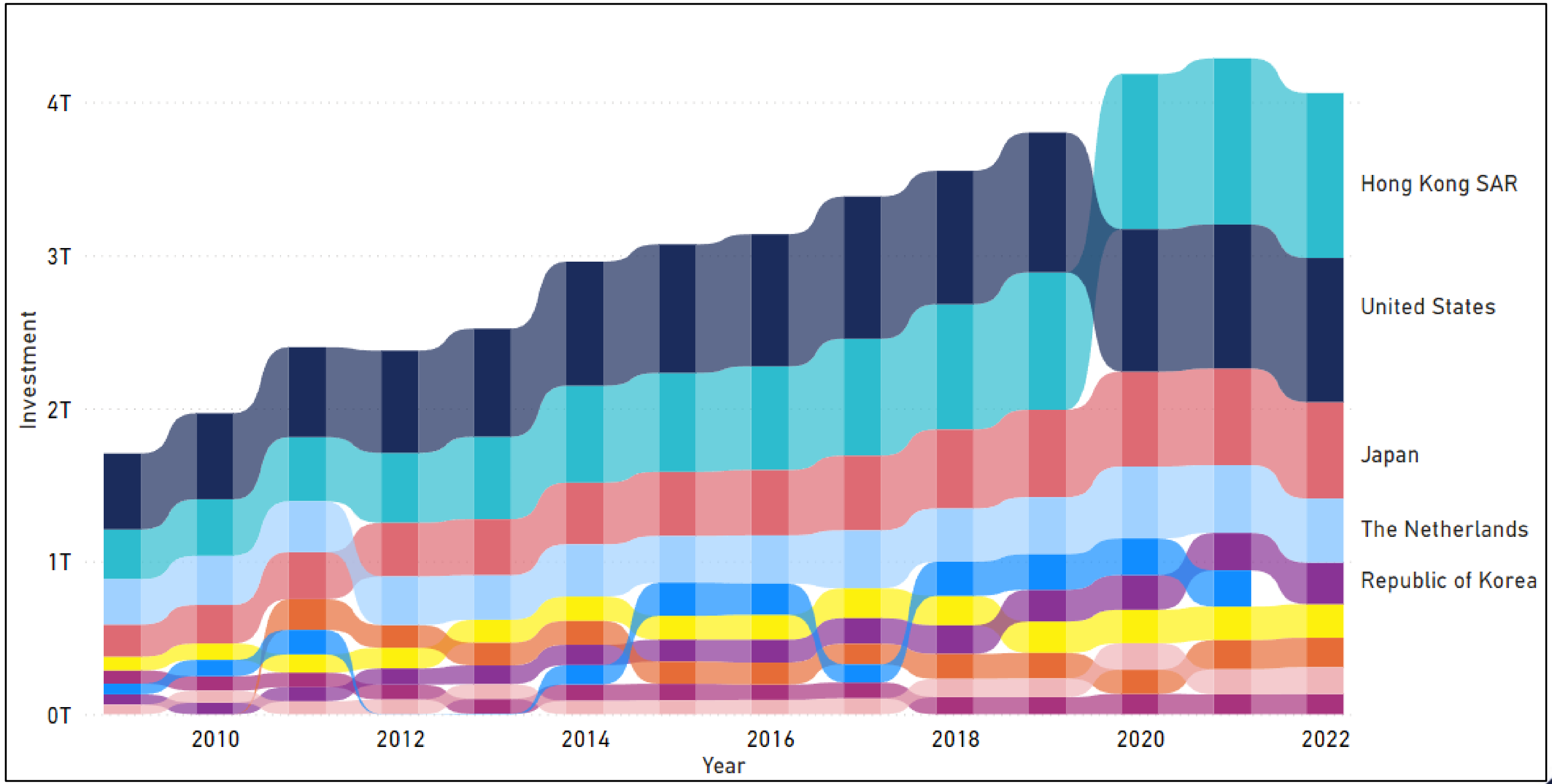


Figure 8. Outward Position of Investing Countries in Developing Asia, 2009 to 2022 (US Dollars)

RESULTS

Nevertheless, we can observe a different trend looking into the different country groups in Developing Asia.

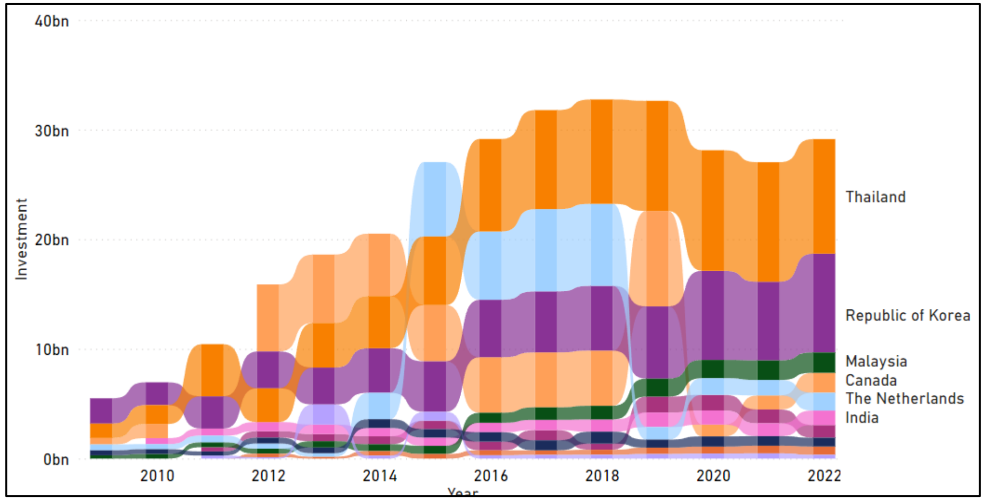


Figure 9. Outward Position of Investing Countries in Frontier Countries, 2009 to 2022 (US Dollars)

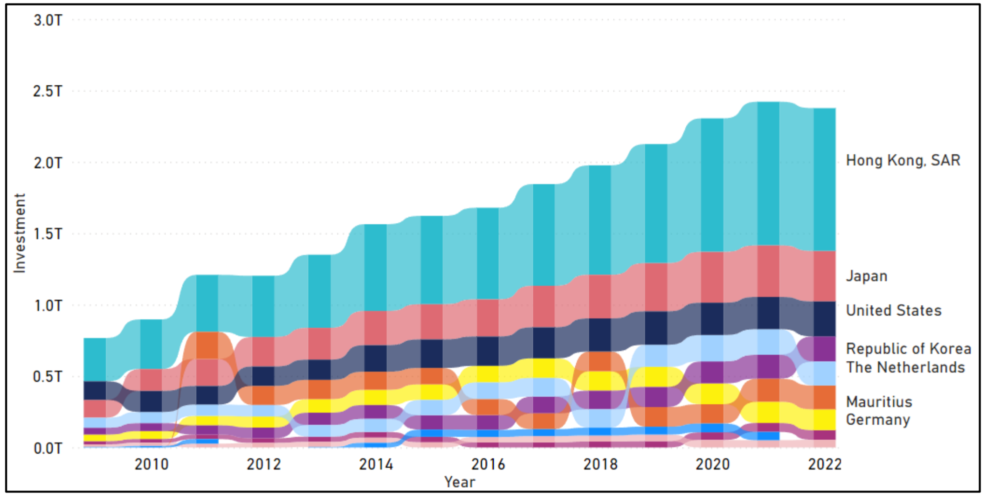


Figure 10. Outward Position of Investing Countries in Emerging Countries, 2009 to 2022 (US Dollars)

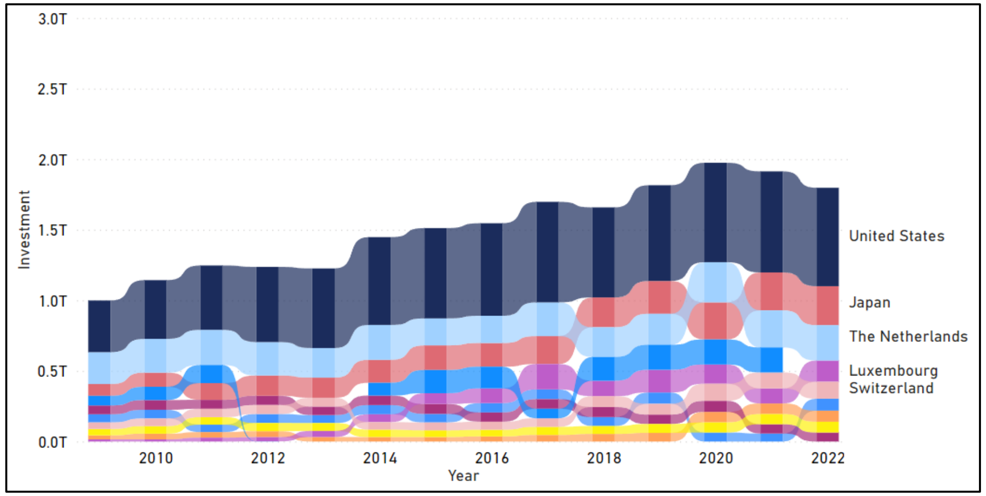


Figure 11. Outward Position of Investing Countries in Advanced Countries, 2009 to 2022 (US Dollars)

RESULTS

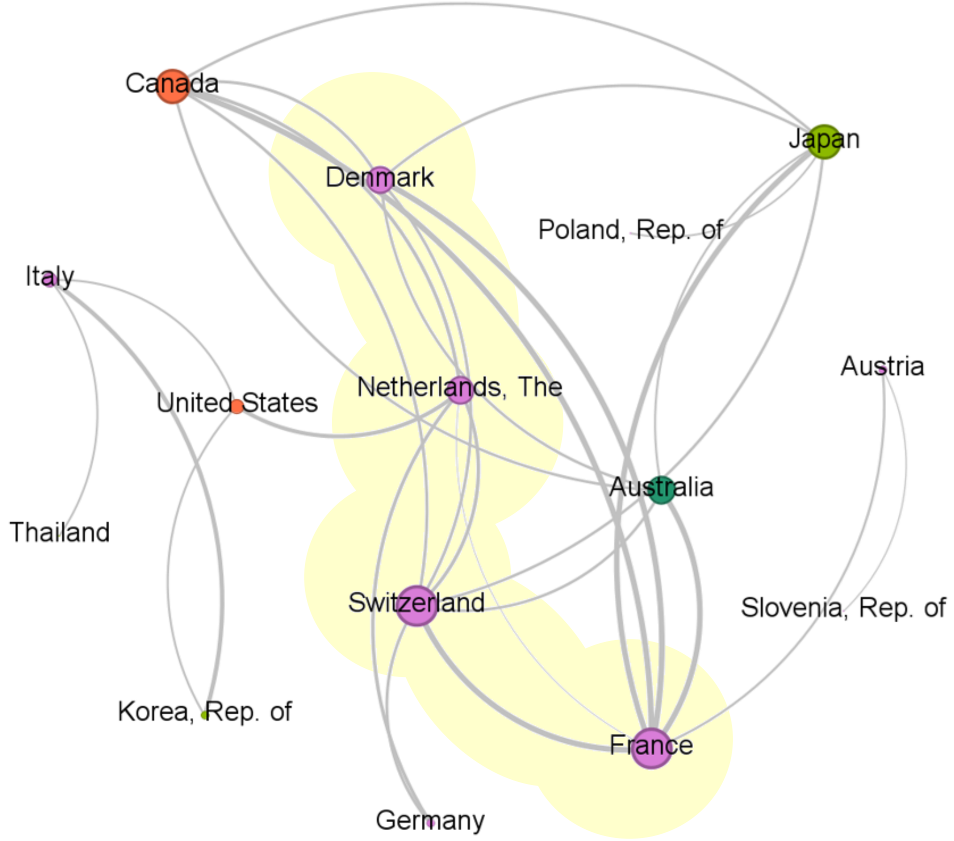
Foreign Investors (the same countries) tend to invest in Hong Kong SAR, Singapore, India and China (the investees) at the same time.

Association Analysis Results

Antecedents	Consequents	Support	Confidence	Lift
Hong Kong SAR	Singapore	0.4619	0.8729	1.6075
Singapore	Hong Kong SAR	0.4619	0.8506	1.6075
India	Singapore	0.4570	0.8416	1.5500
Singapore	India	0.4570	0.8416	1.5500
Hong Kong SAR	China	0.4910	0.9279	1.5257
China	Hong Kong SAR	0.4910	0.8073	1.5257
Singapore	China	0.5000	0.9208	1.5140
China	Singapore	0.5000	0.8221	1.5140
China	India	0.4695	0.7959	1.4657

RESULTS

Switzerland, France, Canada, Japan, Denmark, Australia, and the Netherlands exhibit the same investment behavior towards Asian economies.



Top Five Asian Investment Destinations from Switzerland, France, Canada, Japan, Denmark, Australia, and the Netherlands in 2022	
Country	**FDI Inflows**
Singapore	351,834.28
Mainland China	277,415.98
India	107,488.01
Hong Kong SAR	95,143.74
Thailand	93,962.27

Figure 12. Collaborative Filtering Results
Note: The edges or links are based on the similarity scores, while the nodes or vertices denote the degree or the number of similar countries.

KEY TAKEAWAYS

- Supervised non-linear ML methodologies are effective in identifying the primary features contributing to FDI.
- Extra Trees Regression yielded better R-square of 0.81 compared to conventional econometric models employed in prior research.
- The performance of ML algorithms varies across different subsets of the developing Asian nations.

KEY TAKEAWAYS

Preferred countries (Investees)	Potential Reasons
• Hong Kong SAR • Singapore • India • China	• Trade openness • Favorable tax regimes • Robust infrastructure development • Multilateral trade agreements

KEY TAKEAWAYS

Countries with similar investment behavior (Investors)	Focus
• Switzerland • France • Canada • Japan • Denmark • Australia • The Netherlands	• Technological innovation • Research and development • Infrastructure enhancement • Manufacturing capabilities • Renewable energy

RECOMMENDATIONS

- ML should be further explored to generate new insights, especially in the FDI literature.
- Clustering algorithms can be explored to group countries or sectors with similar FDI behavior.
- Association rule mining can be utilized to identify co-investment or sequential investment patterns in different sectors.

Exploring the Evolving Determinants of Foreign Direct Investment and the Investing Country Preferences in Developing Asian Economies using Machine Learning

Thank you!