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Beyond the Developmental State: Exploring the Variety of Development Models in East Asia*†

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Abstract

East Asia exhibits remarkable economic heterogeneity, yet debates on the region's development have centered predominantly on the most successful cases, such as Japan, South Korea, and Taiwan, all examples of the so-called "developmental state" model, or China's economic upswing. Building on the notion that economic development follows qualitatively different trajectories that give rise to structurally distinct development models across countries, this paper employs a data-driven approach based on a multidimensional cluster analysis of 15 East Asian economies across 12 macroeconomic dimensions for the period 2000-2019 to develop a concise typology of development models in East Asia. In doing so, we find evidence for the presence of four different development models in East Asia: aside from the canonical developmental states (Japan, South Korea, Taiwan), we identify emerging economies (China, Malaysia, Thailand, the Philippines), financial hubs (Hong Kong, Singapore), and peripheral countries (Indonesia, Mongolia, Vietnam, Myanmar, Laos, Cambodia). Our results indicate that findings from past studies focusing on specific cases – such as the countries associated with developmental state model or the rise of China – can be embedded in a more general account that also considers the distinct characteristics and complementary characters of alternative development models present in the same region.

Keywords: Development models, developmental state, cluster analysis, path dependence, East Asia

JEL-Codes: B5, C38, F63, N15, O10

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†Code and data for this paper are published on GitHub and can be accessed via `https://github.com/jakobheibel/development_models_east_asia/`

1 Introduction

East Asian societies are linked by historical exchange and shared cultural contexts, yet the countries in this region vary considerably in their level of economic development. Nations like Japan or South Korea are among the world's richest and most developed nations, while others, such as Myanmar or Laos, belong to the least developed economies, facing economic and political challenges that pose structural barriers to growth (Studwell 2014).

The literature on economic development in East Asia tends to focus on the region's most dynamic economies. The term "economic miracle" was first applied to post-war Japan's rapid industrial transformation (Johnson 1983), and has later been extended to South Korea, Taiwan, and other parts of Southeast Asia. In this spirit, the 1993 World Bank report on *The East Asian Miracle* grouped together "high-performing Asian economies," including Hong Kong, Singapore, South Korea, Taiwan (dubbed the "four tigers"), and the newly industrializing economies of Malaysia, Thailand, and Indonesia (Birdsall et al. 1993, p. 1). In particular, the countries that have emerged as early successful role models of East Asian development – Japan, South Korea and Taiwan – are often associated with a specific development model that focuses on the notion of the "developmental state"(Johnson 1983; Amsden 1989; Wade 1990). However, while these countries serve as the most prominent and clear-cut examples of the developmental state model, the basic notion of state-led economic development, that underpins this model, has also been applied to other countries in the wider literature.[1]

The catch-up processes associated with the "developmental state" model have led to a long-standing debate about the underlying causes of its growth success. As Page (2016) notes, if framed in a neoclassical framework, the core of this debate centers on whether economic development in East Asia has been driven by innovation and productivity growth enabled by interventionist policies and the advantages of catch-up development (Amsden 1989; Johnson 1983; Wade 1990) or whether there was, in fact, no "miracle" at all, and growth was primarily the result of factor accumulation (Birdsall et al. 1993; Krugman 1994).

The debate and controversy on the East Asian development "miracle", with its related focus on the most dynamic and successful economies, has thereby to some degree overshadowed the fact that countries in East Asia actually experience changing and quite heterogeneous growth paths and related developmental trajectories. In other words, there exist more and

[1] As Haggard (2018, p. 1) discusses, the concept of the developmental state has at times been extended to include the development models of Singapore, Hong Kong, and – "somewhat more cautiously" – further South East Asian economies such as Thailand, Malaysia, and Indonesia, "although with some significant debate about whether they fit the developmental state model or not." However, the inclusion of these cases has remained contested (Studwell 2014) as they represent at best partial implementations of the developmental state model. Nevertheless, this debate itself underscores the model's role as an archetypical benchmark for understanding East Asian development.

less successful economies in East Asia and such differences are typically accompanied by qualitatively different developmental trajectories – or development models (Dominy et al. 2025) – that signify heterogeneous forms of specialization and integration of these nations in the global economy.

To illustrate this heterogeneity, Fig. 1 presents our sample of 15 East Asian economies, covering nearly the entire region. The sample encompasses both city-states and demographic giants, authoritarian regimes and consolidated democracies, highly developed economies and some of the world's poorest nations. Growth trajectories vary just as dramatically: while China experienced exceptional expansion during 2000-2019, Japan faced near-stagnation.[2] This extraordinary diversity – spanning economic, political, and demographic dimensions – motivates our central inquiry: What distinct macroeconomic development models characterize these divergent trajectories?

Against this background, this paper is dedicated to studying this heterogeneity of developmental trajectories in East Asia, their temporal persistence, as well as occurrences of structural changes in the form of shifts in development models over time. Thereby, we build on, extend, and complement the existing literature on the developmental state model and the East Asian "miracle" by focusing on the time period 2000-2019, in which the major dynamism of early winners of economic integration was lost. By doing so, we not only explore the relative economic success of the countries following the developmental state model in recent years, but are also able to identify alternative developmental trajectories as well alternative implementations of the developmental state model and, in turn, trace how these fared over time. Moreover, by applying the core notion of developmental models (Gräbner-Radkowitsch 2022; Gräbner et al. 2020a; Dominy et al. 2025) to East Asian countries, the paper also demonstrates the analytical viability of the concept of development models outside of the European context.

While our paper speaks to several aspects of the debate on economic development in East Asia, its primary objective is to identify the distinct development models that characterize the region today. The central research question is: *How can we categorize and conceptualize the variety of development models observed among East Asian economies today?* To address this question, we employ hierarchical cluster analysis based on multiple macroeconomic dimensions to identify development models across East Asian economies. Our approach is similar to those used by Gräbner et al. (2020b) and Dominy et al. (2025) in their respective clustering of European economies, relying on macroeconomic data and

[2] The figure reveals a pattern of relative convergence, with poorer countries achieving higher growth rates (β-convergence). Yet as we demonstrate in Section 4.3, absolute income gaps actually widened during 2000-2019 despite faster growth in poorer countries, reflecting that even substantial growth rate differentials may not suffice to close large initial income disparities in absolute terms. Moreover, and of suggestive interest, Section 4.3 hints at a negative association between growth and democratic governance, though this relationship is not the focus of our analysis.

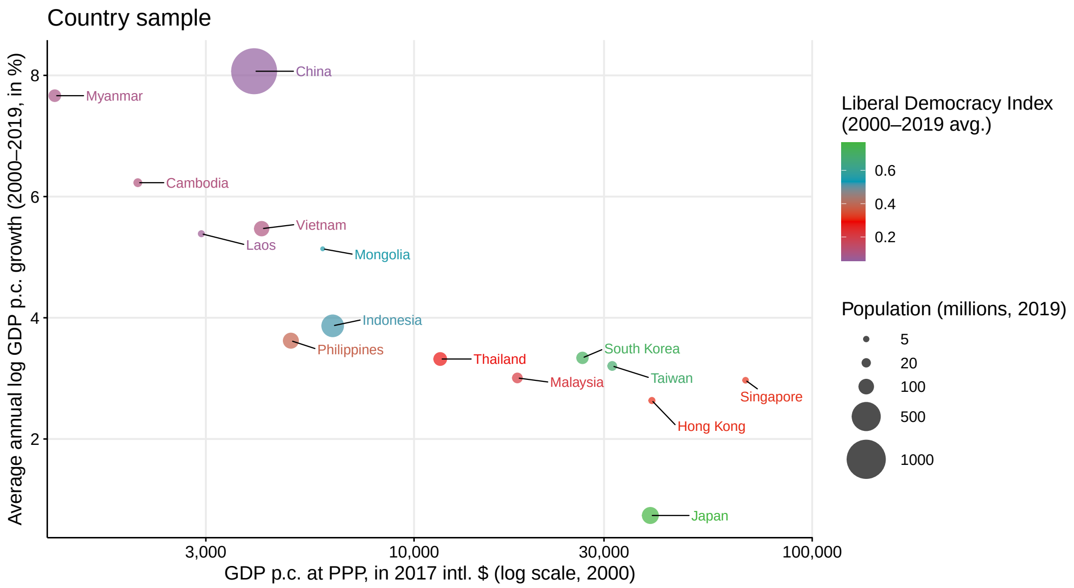


Figure 1: Economic convergence in East Asia, 2000-2019

The figure shows the relationship between initial GDP per capita (2000) and average annual GDP growth (2000-2019) for East Asian economies. Bubble size represents population size. Bubble color indicates the level of democratic governance as measured by the Liberal Democracy Index (V-Dem), where darker shades represent more democratic systems. The plot reveals a pattern of convergence, with poorer countries achieving higher growth rates on average. Data sources: Population data is from the Penn World Table 10.01 (Feenstra et al. 2015), the Liberal Democracy Index is from the V-Dem Varieties of Democracy dataset (Coppedge et al. 2025), data for per capita GDP (at PPP in constant 2017 international dollars) and GDP growth are from the IMF World Economic Outlook, October 2024. Averages are based on own calculations.

estimated country-level fixed effects as input dimensions.[3]

The period of investigation (2000-2019) lies well beyond the growth takeoff of economies such as Taiwan or South Korea. However, drawing on the concept of path dependence, it can be argued that the country classifications derived from this period remain informative of broader development trajectories. Path dependence implies that earlier development patterns and institutional choices continue to shape economic structures and outcomes, making it possible to trace the legacy of past development models even in the more recent data used in this study (Kaldor 1980; David 2007).

Our analysis identifies four distinct development models in contemporary East Asia. (1) Japan, South Korea, and Taiwan comprise the most canonical cases of the *developmental state model*, which remain grouped together. (2) China, Malaysia, Thailand, and the

[3]All computations are conducted in `R`. Because of their similar approaches, the code of this study draws heavily on the public available repositories: `https://github.com/graebnerc/structural-change.git` for Gräbner et al. (2020b) and `https://github.com/dominyj/EconomicPolarizationEU2025.git` for Dominy et al. (2025).

Philippines represent *emerging economies* with incomplete implementations of this model. (3) Hong Kong and Singapore eventually pursued an alternative pathway centered on *finance* and trade rather than manufacturing – a strategy sometimes conflated with the developmental state model in some accounts despite fundamental structural differences (Haggard 2018). (4) Finally, Indonesia, Mongolia, Vietnam, Myanmar, Laos, and Cambodia constitute the *periphery*, largely dependent on primary sectors.

The remainder of this paper is structured as follows: Section 2 reviews the literature on late development in East Asia and introduces the developmental state framework as a theoretical blueprint, guiding our selection of variables that capture countries' adherence to or deviation from this model. Section 3 outlines the clustering methodology and describes the data. Section 4 presents the cluster results and interprets the four development models. Section 5 concludes.

2 Developmental States and Development Models

The remarkable economic transformations in East Asia over the past five decades have repeatedly raised the question which driving factors underlie the development of the most dynamic economies – Japan, South Korea, Taiwan or, more recently, China – in the region. Besides geographical proximity and shared cultural influences, a key similarity in the development history of these countries is the active role of the state.

Against this backdrop, the developmental state concept emerged to explain the remarkable transformation of Japan, South Korea, and Taiwan (Johnson 1983; Amsden 1989; Wade 1990). This transformation involved not only sustained high economic growth , but also a transition of industrial structures from agriculture-dominated exports into high-tech products (Wade 1990). In contrast to dominant neoclassical explanations of economic development, that focus on comparative advantage, market liberalization reforms, and prudent macroeconomic policy to explain the East Asian miracle (Birdsall et al. 1993; Irwin 2023; Koyama/Rubin 2022), the developmental state approach assigned the state a proactive role in steering economic activity towards a national development goal.[4] At its core, the developmental state describes a specific development model that builds on a "centralized state interacting with the private sector from a position of preeminence so as to secure development objectives." (Wade 1990, p. 26).

This model rests on five interconnected pillars that distinguish it from both market-led and socialist systems: First, comprehensive *land reform*, implemented prior to economic takeoff, that creates more egalitarian social structures, boosts agricultural productivity, and generates domestic demand for manufactured goods (Studwell 2014). Second, a *powerful and autonomous bureaucracy* capable of guiding markets through selective resource allocation to designated industries, with support conditional on firm performance in areas such as export targets and technology adoption (Johnson 1983; Amsden 1989; Wade 1990). Third, a *highly regulated financial system* characterized by capital controls and financial repression, deliberately channeling resources from consumption to industrial investment at below-equilibrium interest rates (Haggard 2018; Studwell 2014). Fourth, aggressive *export promotion* through multiple policy instruments, including multiple exchange rate regimes, tax exemptions, subsidies, and preferential credit (Johnson 1983; Amsden 1989; Wade 1990). Finally, *private ownership* within a state-guided framework which deliberately distorts market signals to incentivize long-term capability building over short-term profits.

All these elements are aimed at inducing a process of technological upgrading, i.e., jumping

[4]The developmental states model heavily draws on older theories of state-led development, such as Alexander Gerschenkron's insights into catch-up growth and the need for state intervention especially in the domain of finance (Amsden 1989; Amsden 2001), Friedrich List's advocacy for infant industry protection (Wendler 2008), and other propositions related to the German Historical School (Chang 2003). Key aspects of this approach have since become more integrated into the economic mainstream, see, e.g., Rodrik (1995).

into more sophisticated and higher value-added activities (Hidalgo et al. 2007) within the manufacturing sector's value chains, which are considered as "the heart of modern economic growth" (Amsden 2001, p. 2). As Amsden (2001) emphasizes, learning was the key mechanism that enabled countries with late industrialization to grow and partially catch up with the more advanced economies of the West. The state subsidizes learning, forces firms to export before they are competitive, and channels resources to sectors with no current comparative advantage but high future potential. This strategy's success is evident in the progression of Japan, South Korea, and Taiwan to the highest levels of economic complexity, surpassing many countries that experienced early industrialization, but also evident for the case of China, which mimicked this part of the developmental state strategy in recent decades (Rodrik 2006; ten Brink 2019).

This description of the developmental state as a specific development model can be situated in a larger literature that tries to group countries into distinct variants of capitalism that are associated with different developmental trajectories. Examples for such approaches include the varieties of capitalism approach (focusing on industrial relations, labor market institutions, and the welfare state, see Hall/Soskice 2001),[5] the growth model approach (focusing on drivers of aggregate demand, see Baccaro/Pontusson 2016; Baccaro/Hadziabdic 2024), the World-Systems approach (focusing on the relative position of countries within the hierarchy of global value chains, e.g. Chase-Dunn et al. 2000) or regulation theory (focusing on the interplay between institutions, distribution and accumulation dynamics, see Aglietta 1976; Boyer 2022). Recent extensions of this comparative approach include work on state-permeated capitalism (Nölke et al. 2019; ten Brink 2019), which analyzes how state actors directly coordinate economic development in emerging economies, sharing key similarities with the developmental state model but extending the analysis beyond the classic Northeast Asian cases.

While each of these approaches would probably emphasize specific aspects of the developmental state as a development model, all of them suggest that cases of strong economic dynamism – as associated with the archetypical development state model – typically emerge with complementary developmental trajectories that either have a qualitatively different orientation or are less successful, albeit imitating the dominant approach. And indeed, empirical analysis for Europe (Gräbner et al. 2020b; Dominy et al. 2025) suggests that the most successful countries in terms of exports and manufacturing – an "economic core" that consists mainly of German-speaking and Nordic countries – is complemented by three other developmental trajectories across European countries: first, there exists a group of *workbench economies*, that partly emulate the success of core countries, albeit occupying less profitable niches within global value chains. Second a group of *financial*

[5] Carney (2016) offers an extension of the framework of capitalist ideal types to several East Asian economies.

hubs emerged, that are more oriented towards attracting financial capital and investments by multinational companies, thereby surpassing the core in terms of income. Finally, the *periphery* is unable to emulate the success of core countries and shows, on average, higher unemployment, less growth, and less success on export markets. These clusters are relatively stable over time, thereby pointing to the fact that such developmental trajectories are typically path-dependent, which makes regime-switches improbable, but not impossible. A clear-cut example for the European case is France, which started out as a core country in the early 2000s, but has, over time, become more similar to other Southern European periphery countries.

In a similar vein, this paper argues that while the developmental state model proved remarkably successful in North-East Asia, not all countries could or did follow this path. The model's specificity helps explain why other East Asian economies followed different trajectories. We argue that these alternative pathways can be understood as alternatives to, variations from or failures to implement the developmental state blueprint – each representing a different response to the challenge of late development under varying structural conditions. However, these heterogeneous responses and implementations have created distinct trajectories that became largely persistent over time. While the developmental state literature provides deep insights into successful industrialization, it may not capture the full heterogeneity of recent development experiences in East Asia. Our cluster analysis in turn reveals distinct alternatives to the developmental state path, each representing a different response to the challenge of late development.

3 Data and Method: Identifying Country Clusters

To systematically identify development trajectories across East Asia, this study employs agglomerative hierarchical clustering based on country-level characteristics across 12 socio-economic dimensions for the period 2000-2019. Following the methodological approach of Gräbner et al. (2020b) and Dominy et al. (2025), the method groups countries based on similarities in their underlying structural characteristics as captured by country-level fixed effects extracted from panel regressions. To capture the full heterogeneity of development trajectories in the region, our sample extends beyond the canonical developmental state cases (Japan, South Korea, Taiwan) to include almost all of geographical East Asia: China, Malaysia, Thailand, the Philippines, Indonesia, Vietnam, Myanmar, Cambodia, Laos, Mongolia, as well as the city-states of Hong Kong and Singapore.[6]

Hierarchical clustering is particularly well-suited for this research question as it allows for the comparison of countries across multiple structural dimensions simultaneously, capturing the multifaceted nature of development models. By considering a broad set of 12 macroeconomic dimensions – including income levels, technological capabilities, sectoral composition, trade patterns, and inequality measures – this study adopts a more holistic perspective as compared to parsimonious approaches to classifying countries or regions, such as that of J. Weber/Schulz (2022), who base their taxonomy of the European regional economic structure solely on the volatility of per capita GDP growth, or Baccaro/ Hadziabdic (2024), who rely on import-adjusted demand components to identify growth models.

3.1 Assessing Country Heterogeneity by Clustering Fixed Effects

This study follows Dominy et al. (2025) in using a three-step fixed effects clustering approach to identify development models among East Asian economies, building on the foundational work by Gräbner et al. (2020b), who first developed this methodology for analyzing structural differences across European economies.

Our clustering approach rests on a specific understanding of how development models manifest empirically. We identify development models through their *empirical signatures* – persistent, multidimensional patterns across 12 macroeconomic variables covering income levels, technological capabilities, sectoral composition, trade patterns, inequality, and macroeconomic balances. This approach rests on three core premises.

First, development models are systemic configurations where outcomes function as mutually reinforcing components rather than being determined solely by some underlying causes. High manufacturing shares both result from and sustain industrial policies, labor market

[6] For reasons of data availability, Brunei, Timor-Leste, and the Macau special administrative region are excluded from the sample.

structures, and political coalitions. Persistent inequality patterns both reflect and reproduce institutional arrangements. What appears as *outcomes* on one level constitutes an *input* on another.

Second, the fact that key variables exhibit simultaneity and mutual constitution complicates inference. GDP levels, technological capabilities, sectoral structures, trade integration, and inequality are jointly determined and mutually reinforcing. Rather than treating these interdependencies as obstacles to causal inference, we leverage them methodologically: countries following similar development models should exhibit coherent patterns *across all dimensions simultaneously.*

Third, temporal persistence provides evidence for systemic configurations. If (heterogeneous) development models represent stable systems with self-reinforcing mechanisms, they should leave time-invariant (heterogeneous) footprints. Conversely, absent underlying structural coherence, we would observe random fluctuations or inconsistent patterns – countries clustering on some dimensions while diverging on others. The stability and multidimensional consistency of observed patterns thus constitutes evidence for distinct model types.

Empirically, the country-level fixed effects in our panel regressions, which are based on Equation (1), capture these time-invariant, country-specific patterns. Statistically, they represent each country's average position on a given dimension over 2000-2019 after controlling for shared time trends. Conceptually, we interpret them as structural characteristics that, in their multidimensional configuration, provide indication for the underlying development models. The cluster analysis then identifies the latent grouping structure implicit in these patterns – revealing which countries exhibit similar configurations across all dimensions and whether distinct model types exist. In a second step we can then examine in greater detail for the empirical properties associated with distinct development models.

Hence, this method does not claim to directly observe or isolate the institutional arrangements, policy interactions, feedback mechanisms, or historical legacies that constitute development models. Rather, these deeper determinants remain partially unobserved, but are reflected in the empirical signatures exhibited by our methodological approach. Thereby, systemic configurations – precisely because they involve mutually reinforcing elements – generate persistent, multidimensional outcome patterns that serve as those empirical signatures. Thus, our approach identifies development models through these signatures, treating the observed constellation of outcomes as directly informative about underlying structural types.

The method proceeds through three sequential steps:

Step 1: Fixed Effects Estimation For each of the 12 socio-economic variables k, we estimate country-level characteristics using panel regressions

$$Y_{it}^{k} = Country_{i}^{k} + Year_{t}^{k} + \epsilon_{it}^{k} \tag{1}$$

where Y_{it}^{k} denotes variable k for country i and year t, $Country_{i}^{k}$ captures time-invariant characteristics (country fixed effects), $Year_{t}^{k}$ controls for common time trends (year fixed effects). Estimating without intercept ensures each country has its own baseline level. Standard errors are clustered at the country level to account for within-country correlation.

The country fixed effects thus represent each country's average time-invariant structural characteristics and serve as input for identifying development model clusters in the subsequent analysis.

Step 2: Distance Matrix Rather than treating all estimated differences equally, we employ the uncertainty-weighted distance measure introduced by Dominy et al. (2025):

$$d_{ijk} = \frac{|FE_{ik} - FE_{jk}|}{\sqrt{SE_{ik}^{2} + SE_{jk}^{2}}} \tag{2}$$

where the absolute difference in fixed effects between two countries i and j in dimension k is normalized by their combined standard errors from the model as specified in Equation (1). Overall distances between countries are calculated as averages of these standardized differences across all dimensions. This weighting gives precisely estimated differences (lower standard errors) more influence than noisily estimated ones, reducing the impact of statistical noise on final estimates. It also handles missing data systematically: by treating missing estimates as completely uncertain (essentially infinite standard errors, yielding zero weight), the metric directly accounts for incomplete data.

Step 3: Hierarchical Clustering In the final step, we apply agglomerative hierarchical clustering to group countries based on the distance matrix from Step 2. Countries with similar patterns across all 12 dimensions are grouped into the same cluster, while structurally distinct countries form separate clusters. Following Gräbner et al. (2020b) and Dominy et al. (2025), we employ Ward's method, which minimizes within-cluster variance while maximizing between-cluster differences. This produces compact, internally homogeneous country groups where each cluster represents a distinct development model.

Variable	**Scaling Factor**	**(Main) Source**
Economic Complexity Index	0.1383	The Atlas of Economic Complexity (The Growth Lab at Harvard University 2025)
GDP p.c (at PPP in constant 2017 international dollars, deviation from sample mean)	0.1312	IMF World Economic Outlook, October 2024
Share of financial & insurance activities in total gross value added	0.1068	Compiled from various sources, see Table A2 in the appendix for more details
Exports of goods and services (% of GDP)	0.0967	World Development Indicators, World Bank
Share of mining & quarrying in total gross value added	0.0842	Compiled from various sources, see Table A2 in the appendix for more details
Gini on market income	0.0798	Standardized World Income Inequality Database (Solt 2022)
Unemployment rate	0.0712	World Development Indicators, World Bank
Share of manufacturing in total gross value added	0.0712	Compiled from various sources, see Table A2 in the appendix for more details
Share of agriculture, forestry and fishing in total gross value added	0.0667	Compiled from various sources, see Table A2 in the appendix for more details
FDI inflows (% of GDP)	0.0641	UN Trade and Development (UNCTAD)
Current account balance (% of GDP)	0.0494	World Development Indicators, World Bank
Public debt (% of GDP)	0.0404	Global Debt Database, IMF (Mbaye et al. 2018)

Table 1: List of variables, scaling factors, and data sources

The variables are sorted according to their scaling factor. Detailed comments on the sources and the compilation of the data can be found in Appendix A. The scaling factors are the normalized variable weights used by the distance calculation for the FE clustering.

3.2 Variables and Data

Table 1 presents the 12 socio-economic variables and their respective data sources used in the cluster analysis, covering key macroeconomic indicators, sectoral composition, inequality measures, and technological capabilities for 15 East Asian economies over 2000-2019. Our analysis focuses on this period for two complementary reasons. First, as shown in Figure 1, this period captures the convergence phase following the 1997 Asian financial crisis, when divergent development trajectories among East Asian economies became increasingly apparent. Second, data coverage for our key variables – particularly the Economic Complexity Index and GDP per capita – is comprehensive for all sample countries during this period. By ending the analysis in 2019, we exclude the immediate impacts of the COVID-19 pandemic, which may have produced country-specific short-term distortions unrelated to structural development models. More detailed comments on the sources of all variables and the compilation of the data can be found in the appendix, specifically in Table A1. Details on the data sources used for compiling the data on the different sector or industry shares in total gross value added in specific is also available in the appendix, see Table A2 and Table A3.

Variable selection in cluster analysis critically shapes outcomes, as emphasized by Giordani et al. (2020). Our baseline specification of 12 variables emerged through an iterative process combining theoretical insights from the developmental state literature with empirical refinement. We include GDP per capita (measured as deviation from sample mean), the Economic Complexity Index (Hidalgo/Hausmann 2009), sectoral value-added shares (manufacturing, finance, mining, agriculture), trade openness, FDI flows, inequality measures, unemployment, current account balance, and public debt. This combination aims to capture the multifaceted nature of East Asian development models while avoiding variables that might mask relevant structural differences.

The uncertainty-weighted distance measure described above helps mitigate concerns about variable selection by incorporating estimation precision directly into the clustering procedure. Variables with high statistical uncertainty are automatically discounted when determining country distances, reducing the impact of noisy or poorly estimated indicators. To illustrate the practical effect of this uncertainty weighting, Table 1 shows scaling factors that reveal each variable's resulting contribution to country distinctions.[7] In this analysis,

[7] Scaling factors are computed ex-post to quantify each variable's effective weight in the distance metric. For each variable k, we calculate

$$w_k = \frac{2}{N \cdot (N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(\sqrt{SE_{ik}^2 + SE_{jk}^2} \right)^{-1},$$

which averages the inverse combined standard errors across all country pairs (i, j). These values are then normalized across variables to sum to one: $\tilde{w}_k = w_k / \sum_{k=1}^{K} w_k$. See Dominy et al. (2025) for further discussion.

the ECI (0.138) and GDP per capita deviation (0.131) emerge as the most discriminatory variables, while public debt (0.040) contributes least to country distinctions.

However, even variables with low scaling factors can influence cluster results if they capture unique structural features not reflected in other indicators. Recognizing these methodological considerations, we pursue transparency by systematically testing alternative variable specifications in Section 4.4, where we examine how country classifications change under different variable selections.

Country	**Variable**	**Missing Years**
Hong Kong	Public debt (% of GDP)	2000
South Korea	Public debt (% of GDP)	2019
Mongolia	Public debt (% of GDP)	2000-2005
Myanmar	Exports of goods and services (% of GDP)	2000-2009
Myanmar	Gini on market income	2000-2009; 2018-2019
Thailand	Public debt (% of GDP)	2000-2004
Cambodia	Gini on market income	2013-2019
Laos	Exports of goods and services (% of GDP)	2017-2019
Laos	Gini on market income	2019

Table 2: Variables not covering the complete period 2000-2019

Data for the years 2000-2019 could be recovered for most variables and countries. However, some exceptions exist. These are shown in Table 2. In particular, data points are missing for the periphery countries Myanmar and Laos, as well as observations on public debt and income inequality. For most countries where the coverage is not complete over the period 2000-2019, only a few years of observations are missing, e.g. data for public debt as a percent of GDP in Hong Kong is only available from 2001, while South Korea misses the entries for the years 2019 and onward for this variable.

To provide initial insight into the structure of our input data before entering the clustering procedure, Fig. 2 examines the correlation patterns among country-level fixed effects. These fixed effects are the time-invariant structural characteristics that, after standardization as described in step 2, form the basis for our distance calculations in the clustering procedure. Variables are hierarchically ordered by their absolute correlations (Ward's method, distance $= 1 - |r|$), with rectangles indicating blocks of closely related dimensions. The correlations reveal how different structural dimensions co-vary across countries (between-country variation) after controlling for common time trends.

These correlation patterns provide initial empirical support for our methodological rationale: if development models represent coherent systemic configurations, we should observe systematic co-variation across dimensions rather than independent variation. Indeed, many dimensions exhibit substantial correlations – both positive (e.g., finance, exports, and FDI: $r > 0.7$) and negative (e.g., agriculture and ECI: $r = -0.89$) – indicating that countries occupy structured positions rather than random locations in the multidimensional space. The hierarchical grouping reveals blocks of closely related dimensions, suggesting that variation is structured along major underlying axes rather than a single development continuum. In particular, a development gradient driven by technology and investment (from primary sector dependence to technological sophistication) appears to intersect with qualitatively different patterns of global integration (manufacturing-oriented versus finance-trade-oriented). Such instances of multidimensional structuring motivate our clustering approach.

However, high correlations also raise the question whether some variables measure similar underlying dimensions, potentially leading to double-counting in the cluster analysis. Our robustness tests (Section 4.4) systematically address this concern by examining alternative variable specifications. These tests demonstrate that the cluster structure remains stable even when excluding highly correlated variables, indicating they contribute independent information despite their associations.

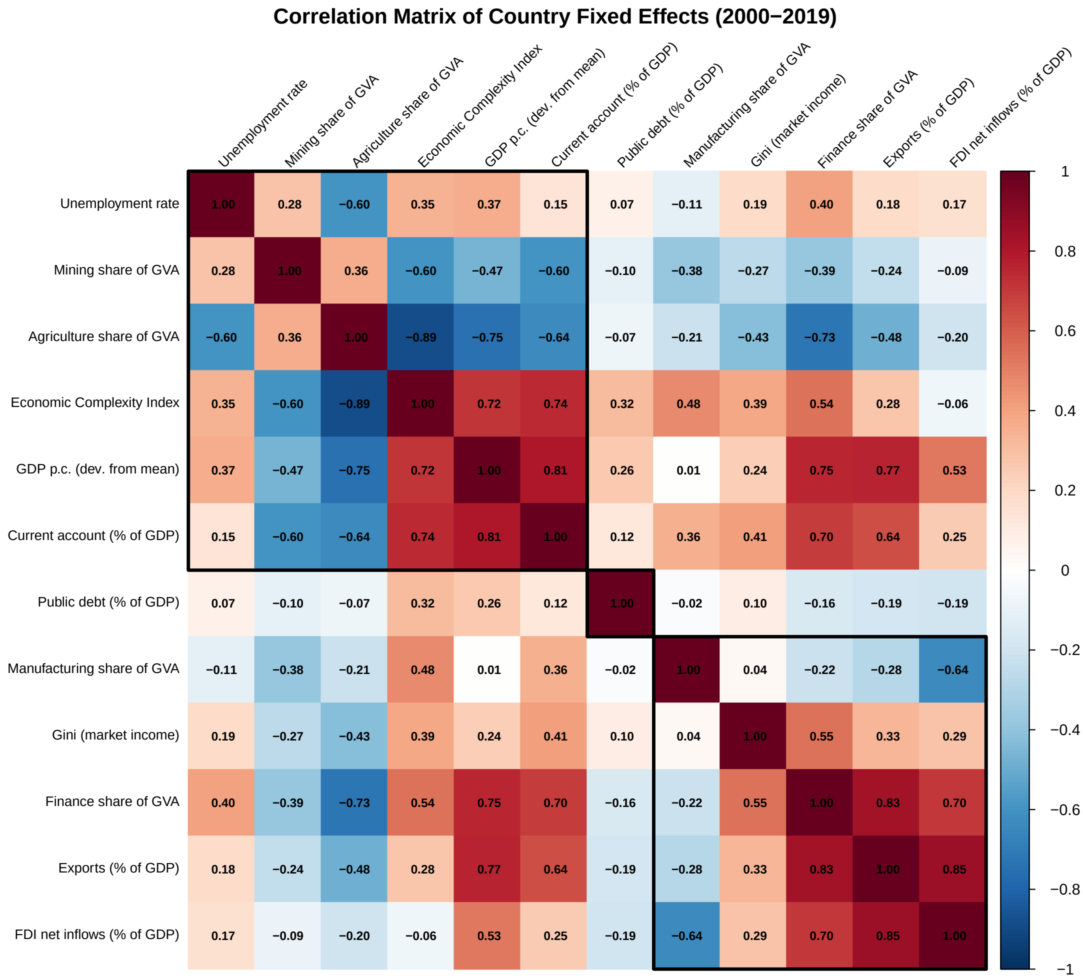


Figure 2: Correlation matrix of country-level fixed effects (2000–2019)

This figure displays Pearson correlation coefficients between country-level fixed effects across the 15 East Asian economies. Variables are hierarchically ordered using Ward's method on the distance matrix ($1-|r|$). Rectangles indicate variable groupings at a specified cut level, highlighting blocks of dimensions with strong mutual correlations. Coefficients range from -1 (dark blue) to $+1$ (dark red), with values displayed in each cell.

4 Results and Discussion: Identifying Development Trajectories

This section presents and discusses the results of the FE clustering, which distinguishes four groups among the 15 East Asian economies in our country sample. To aid the interpretation, an alternative visualization of the cluster results based on multidimensional scaling (MDS) analysis as well as loading vectors, showing the correlations between the scaling dimensions and the underlying economic variables, has been employed in addition to traditionally used dendrograms. Comparative statistics further highlight the distinctive characteristics of each identified development model. Finally, we assess robustness across time and alternative variable specifications using Sankey diagrams, indicating the stability of the results.

4.1 Results of the Country Clustering

Fig. 3 displays the results derived from the FE clustering. The dendrogram visualizes the four country groups as well as their relative distances to each other. The clustering identifies four distinct development models: (1) the developmental states of Japan, South Korea, and Taiwan; (2) the financial hubs Hong Kong and Singapore; (3) the emerging economies comprising Malaysia, Thailand, the Philippines, and China; and (4) East Asia's periphery, consisting of Indonesia, Mongolia, Vietnam, Myanmar, Laos, and Cambodia.

A critical question in hierarchical clustering concerns determining the optimal number of clusters – essentially deciding where to make the cut in the cluster tree. While formal statistical measures provide guidance, the choice ultimately depends on the research question and thus remains "subjective" and dependent on "the level of granularity the researcher is looking for" (Giordani et al. 2020). This study therefore combines visual inspection of the dendrogram with formal statistical diagnostics and theoretical considerations.

In our results, four groups among the sample size of 15 countries can be well distinguished along the lines of the key structural differences, and thus seems to be a reasonable level of granularity to assume. The dendrogram serves as a first intuitive way of identifying distinct groupings and visually confirms that the four-cluster solution is justified. The four groups can be well distinguished visually at the height of 7.19 (in Ward's method, height represents the total within-cluster variance after merging clusters at each step). At this level, the four clusters show clear separation, while alternative configurations (more or fewer groups) would require cuts at considerably different heights: choosing five clusters would subdivide the periphery, while choosing three clusters would merge the developmental states with the emerging economies.

Multiple statistical indicators support this visual assessment, pointing to the existence of

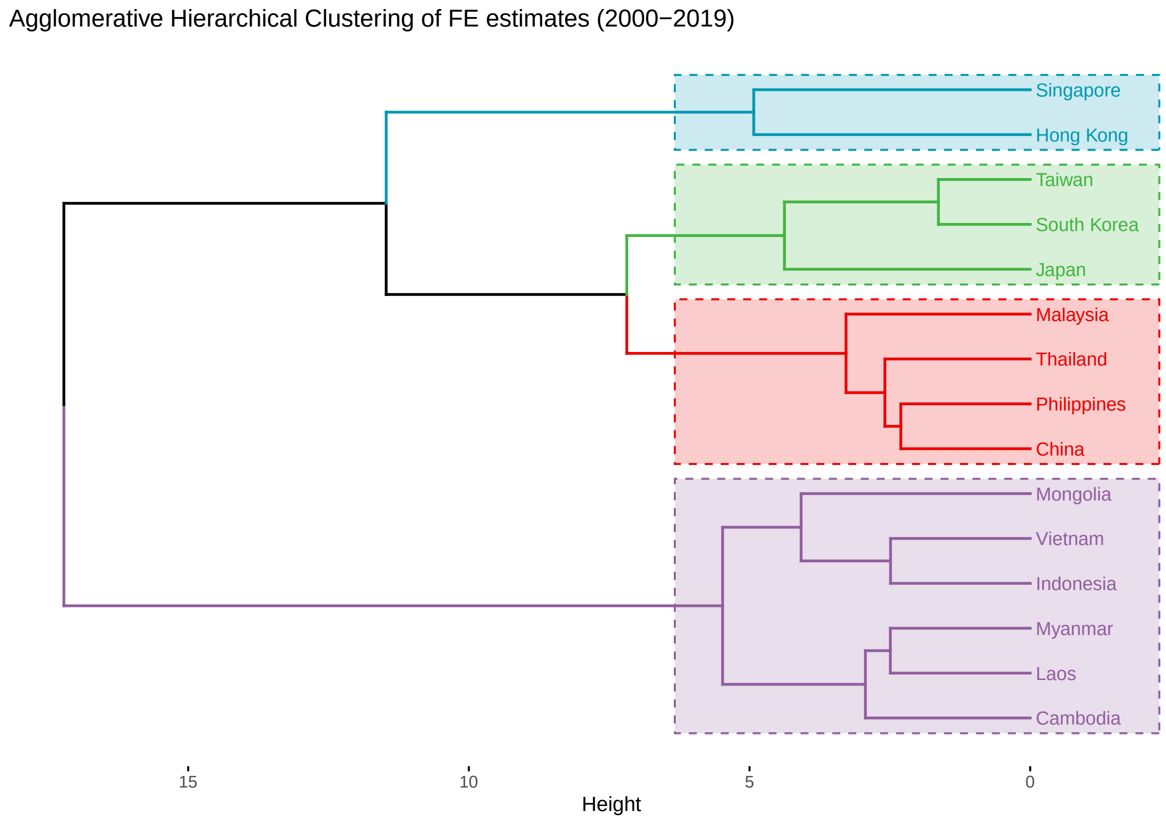


Figure 3: Clustering of FE estimates

Dendrogram with country classification based on the agglomerative hierarchical clustering of country-level fixed effects (see the model presented in eq. (1)*).*

four distinct country groups in our sample. Specifically, Fig. A1 in the appendix visualizes the heights at each agglomeration step to illustrate differences between successive mergers; Fig. A2 compares the changes in within-cluster dispersion between different numbers of clusters; and Fig. A3 presents the results of the gap statistic introduced by Tibshirani et al. (2001), which identifies four groups as the optimal number of clusters. A detailed discussion of these indicators and their graphical representations is provided in Appendix A.1.1.

4.2 Multidimensional Scaling and Factor Map

To better understand the structural relationships between country clusters and their underlying economic characteristics, we employ multidimensional scaling (MDS) analysis on the distance matrix derived from our clustering procedure. This approach allows us to visualize the high-dimensional clustering space in two dimensions while preserving the relative distances between countries as accurately as possible. The resulting factor map (Fig. 4) provides both, a spatial representation of country positions as well as insights into the economic variables driving cluster formation by plotting variable loading vectors.

The MDS analysis is based on the same weighted distance matrix used for hierarchical

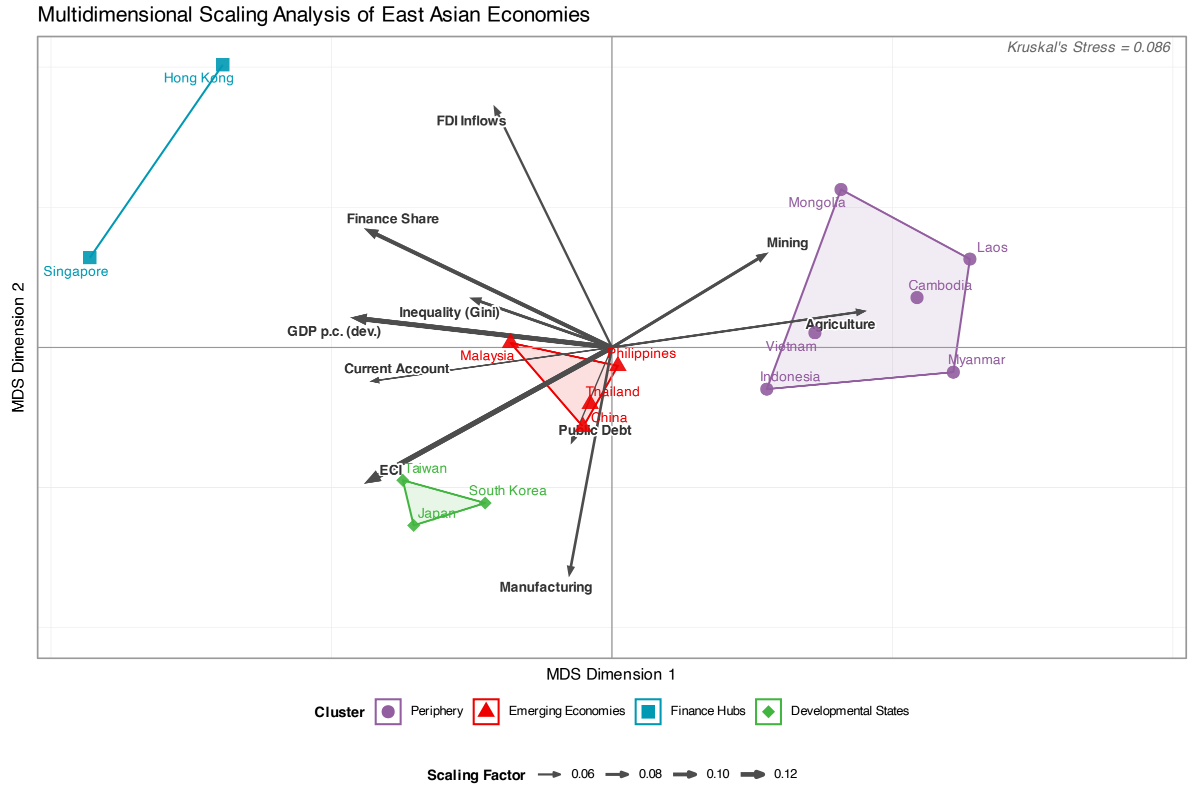


Figure 4: MDS Factor Map: Spatial Arrangement of East Asian Countries by Economic Characteristics

Notes: Multidimensional scaling (MDS) applied to the weighted distance matrix from hierarchical clustering. Countries are positioned based on economic similarity, with clusters indicated by colors and corresponding shadings. Arrows represent correlations between economic variables and MDS dimensions, with length indicating correlation strength and thickness reflecting the scaling factor shown in the legend. Kruskal's stress = 0.086 indicates good fit.

clustering, which incorporates the standard errors of our panel estimates to weigh variables by their statistical precision. We apply classical multidimensional scaling to project the countries into a two-dimensional space that minimizes the distortion of pairwise distances.[8] Quality measures indicate that the projection preserves ordinal relationships well (Kruskal's stress: 8.6%) and that distances retain meaningful information, though with some compression (metric stress: 19%; details in appendix A.1.2). The factor map is thus well-suited for visualizing cluster relationships.

The four clusters occupy distinct regions of the factor map shown in Fig. 4 that align with their economic characteristics. The Financial Hub Cluster (Hong Kong and Singapore) is clearly separated in the upper-left quadrant, reflecting high financial sector development

[8]We use R's `cmdscale()` function, which solves this projection analytically through eigenvalue decomposition. We chose classical over nonmetric MDS to preserve the metric information in our uncertainty-weighted distance matrix; nonmetric alternatives would discard this by treating distances as purely ordinal.

and trade openness with lower manufacturing intensity. The Developmental State Cluster (Japan, South Korea, and Taiwan) forms a compact group in the lower-right quadrant, combining high development levels with strong manufacturing orientation. The Emerging Economies Cluster (Malaysia, Thailand, Philippines, and China) occupies the central region, positioned between developmental extremes with intermediate levels across most economic dimensions. The Periphery Cluster shows the most spatial dispersion in the upper-right quadrant, consistent with this group having the lowest GDP per capita and economic complexity among all clusters. The internal variation largely reflects differences in sectoral composition, with countries positioned along various combinations of agricultural, mining, and early-stage manufacturing specialization.

To provide more intuition on what economic dimensions the MDS space exactly represents, we calculate correlation coefficients between the original economic variables (fixed effects estimates) and the two MDS dimensions (complete correlation values in Table A4). These correlations are visualized as loading vectors in the factor map, with the direction and length of each arrow indicating the strength and direction of the relationship between variables and the dimensional space. For visual clarity, all loading vectors are scaled by a factor of 4, which enhances their visibility while preserving the relative relationships between variables.

The factor map reveals complex economic relationships that can be interpreted through two complementary approaches. Most precisely, the individual loading vectors indicate how a country's properties influence its positioning in the factor map. This creates gradients of economic specialization; for example, countries positioned in the direction of the "FDI Inflows" vector tend to have higher FDI values, while those in the opposite direction have lower or more negative values. The length of each vector reflects the strength of this relationship, with longer arrows indicating stronger correlations with the spatial dimensions. A secondary interpretive approach builds on a rough characterization of the MDS dimensions themselves, while acknowledging that these orthogonal axes represent statistical constructs rather than theoretically derived economic categories.

MDS Dimension 1 (horizontal axis) appears to broadly capture a development gradient, with GDP per capita deviation showing a strong negative correlation (-0.91) and agricultural value-added share showing a strong positive correlation (0.90). This dimension tentatively separates more developed economies (positioned toward the right) from less developed, agriculture-dependent economies (positioned toward the left). Financial sector development also loads negatively on this dimension (-0.87), which aligns well with the observation that financial hubs typically enjoy high incomes.

MDS Dimension 2 (vertical axis) roughly represents what might be characterized as a trade and investment orientation dimension positing countries between specializing either in (financial) services or in technological sophistication. FDI inflows show the strongest positive correlation (0.85), while manufacturing value-added correlates negatively (-0.81). Export intensity also loads positively (0.62) on this dimension. In line with this interpretation poorer countries located on the right show a smaller variation in this dimension, e.g., a less pronounced orientation towards both, financial as well as technological specialization.

While these dimensional interpretations should be understood only as rough approximations of the more precise gradient relationships indicated by the individual loading vectors, the observation that multidimensional aggregation produces conceptually plausible continua in both dimensions is reassuring.

4.3 Interpretation and Stylized Facts

While the factor map provides spatial intuition about country relationships, individual economic indicators offer more concrete insights into these development models. This section examines the development of GDP per capita and the ECI across countries as both proved central to identifying development models, carrying the highest scaling factors (0.1312 and 0.1383) in our clustering approach. In the remainder of this section we present comparative statistics capturing each cluster's defining characteristics.

Note, however, that the cluster classification emerges from multidimensional analysis rather than any single variable. As the robustness analysis in Section 4.4 demonstrates, no individual dimension dominates the clustering results. Nevertheless, these two core indicators effectively capture the fundamental development gradients reflected in our MDS analysis – distinguishing countries by their income levels and technological capabilities. The four clusters broadly align along this gradient, with financial hubs or developmental states occupying top positions, followed by emerging economies, and the periphery. Tracking these indicators from 2000-2019 additionally reveals dynamic patterns of convergence and divergence not visible in the static cluster analysis.

Fig. 5 displays GDP per capita as deviations from the yearly sample mean, illustrating how the four development models occupy distinct hierarchical positions along the income gradient. Countries with absolute per capita income rising faster than the sample average show upward-sloping curves, while those with absolute incomes growing more slowly display downward-sloping trends. Notably, the "widening cone" pattern indicates that absolute income gaps have increased over 2000-2019: the convergence in (relative) growth rates observed in Fig. 1, has not compensated enough for differences in starting positions. The resulting σ-divergence – rising absolute dispersion even as poorer countries grow faster – reflects that substantial growth rate differentials may not suffice to close large initial income disparities in absolute terms.

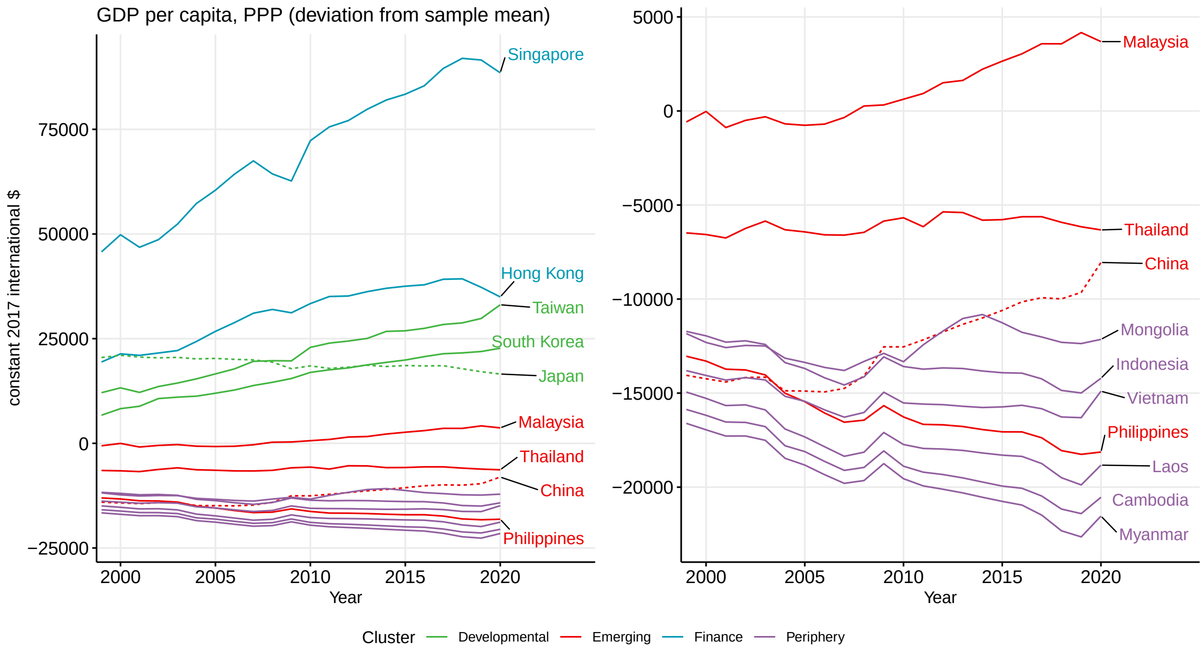


Figure 5: Differences in average income across the country sample

To illustrate trends of economic divergence or convergence, income levels are shown as deviations from the sample mean. The right plot zooms in on the emerging and peripheral economies. Colored groups are from the FE clustering results (Fig. 3). Data source: IMF World Economic Outlook, October 2024.

The four clusters align clearly with the income hierarchy: financial hubs (Hong Kong, Singapore) remain substantially above the regional average throughout the period; developmental states (Japan, South Korea, Taiwan) maintain consistently high positions; emerging economies (Malaysia, Thailand, Philippines, China) cluster near the mean; and periphery countries remain below average. This hierarchical structure persists over time, with two notable exceptions of absolute convergence marked by dashed lines. The Japanese economy has been famously stagnating for several decades and is suffering from a specific set of problems related to contractionary economic policy, tight credit conditions and, correspondingly, insufficient aggregate demand (Krugman 1998) after the burst of the bubble economy in 1989 (Studwell 2014). These add to structural issues like demographic change (Akram 2019). Although slowing down in most recent years, the impressive growth rate that China has experienced since its "reform and opening up" (I. M. Weber 2021; Chow 2004) has set it on a course of absolute convergence with the other countries in the sample. China thus was able to leave the income levels of the periphery behind, catching up to Thailand (and, not shown here, overtaking it in 2023).

Judging just from the GDP per capita data in Fig. 5, the Philippines should seemingly rather be grouped with the periphery, and not the group of emerging economies (in red). However, as discussed with the cluster results, the country is indeed classified together

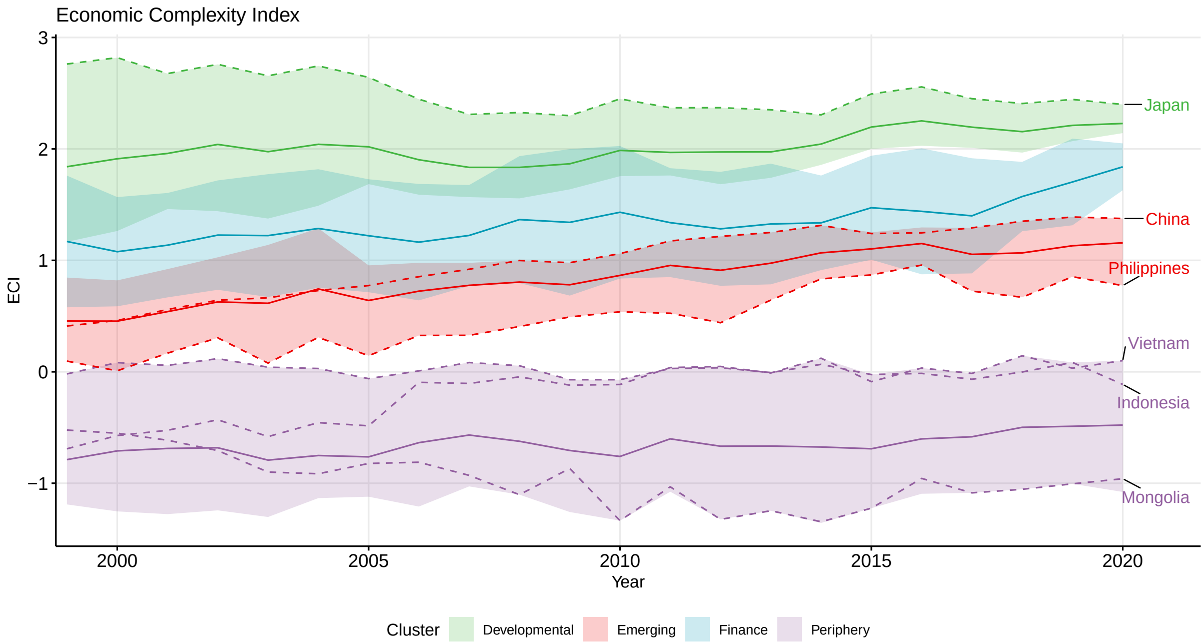


Figure 6: Mean ECI across development models

Mean ECI values (unweighted average across all countries) for each cluster are drawn with solid lines, the ribbons around the means indicate the range between the maximum and minimum values within each country group. Dashed lines highlight values for specific countries. Data source: The Growth Lab at Harvard University (2025), using SITC product classification.

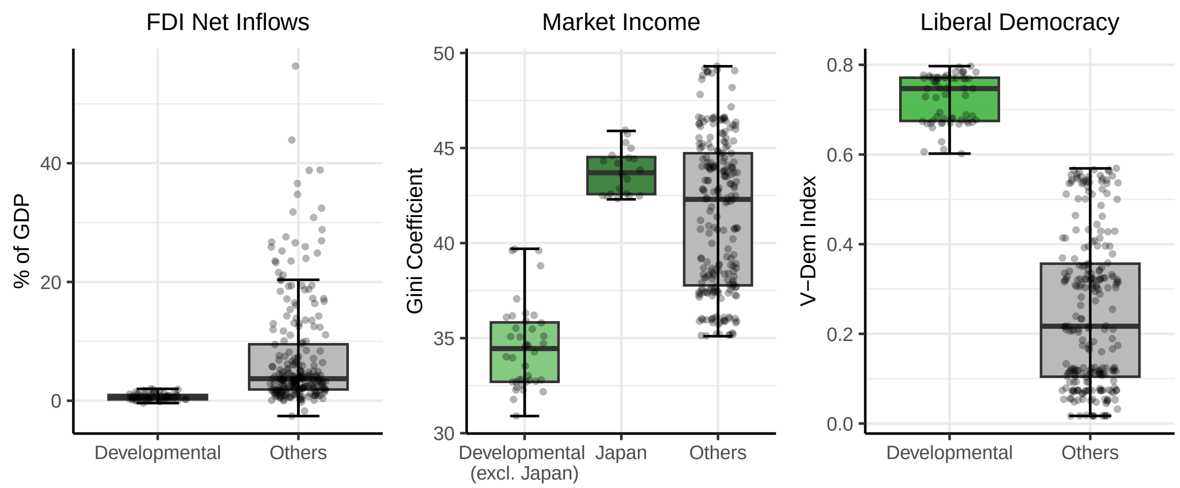
with Malaysia, Thailand, and China, while Mongolia, Indonesia, and Vietnam are assigned to the same cluster as Laos, Cambodia, and Myanmar (Fig. 3).

Fig. 6 indicates that why this assignment is plausible against the backdrop of our consideration of technological sophistication. While the Philippines lag behind in income, they have caught up somewhat to the other Southeast Asian emerging economies in terms of economic complexity. The economic complexity index (ECI) Hidalgo/Hausmann (2009) formalizes the idea that the technological capabilities can be measured by jointly assessing the *rarity* of goods a country produces and exports as well as the *diversity* of its overall product portfolio, reflecting deeper structural conditions for sustained growth (Hartmann et al. 2017).

At the beginning of the study period in 2000, the Philippines exhibited a level of technological sophistication similar to that of Indonesia. However, while Indonesia stagnated in this respect over the following two decades, the Philippines experienced a significant expansion of technological capabilities. A similar trajectory to that of the Philippines, albeit on a lower level, can also be observed for Vietnam, which surpassed Indonesia in the 2010s to become the leading country within the periphery group in terms of the complexity of its production structure. Overall, however, the gap between the periphery countries and the other groups continued to widen throughout the period of investigation.

Taken together, the pattern shown by the ECI aligns well with the broader cluster results: Developmental states demonstrate the highest technological capabilities, driven by successful state-led policies promoting high-tech manufacturing. Financial hubs occupy intermediate positions, their lower complexity relative to income reflecting specialization in services rather than manufacturing. Emerging economies cluster around intermediate ECI values, led by China since the mid-2000s. The periphery remains at the bottom, and the widening gap to the other clusters highlights that most of these countries are not only behind in absolute income levels but are also falling further behind in technological capabilities.

(a) Developmental States Characteristics



(b) Emerging Economies Characteristics

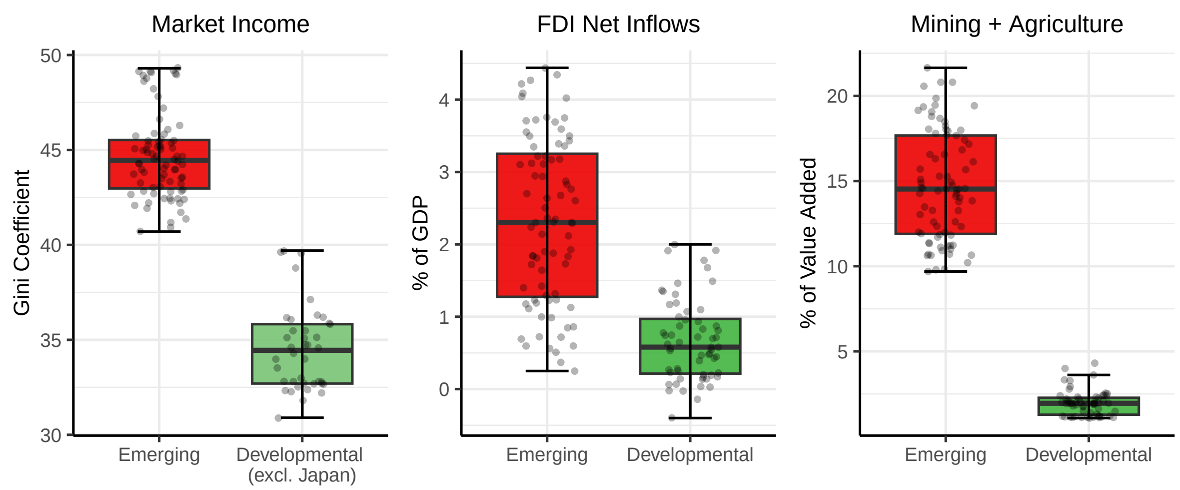
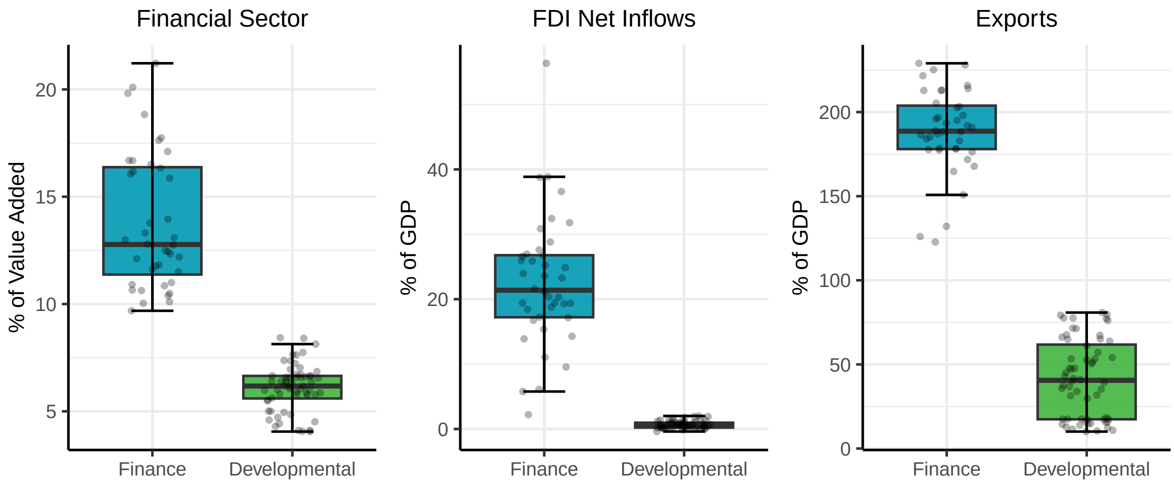


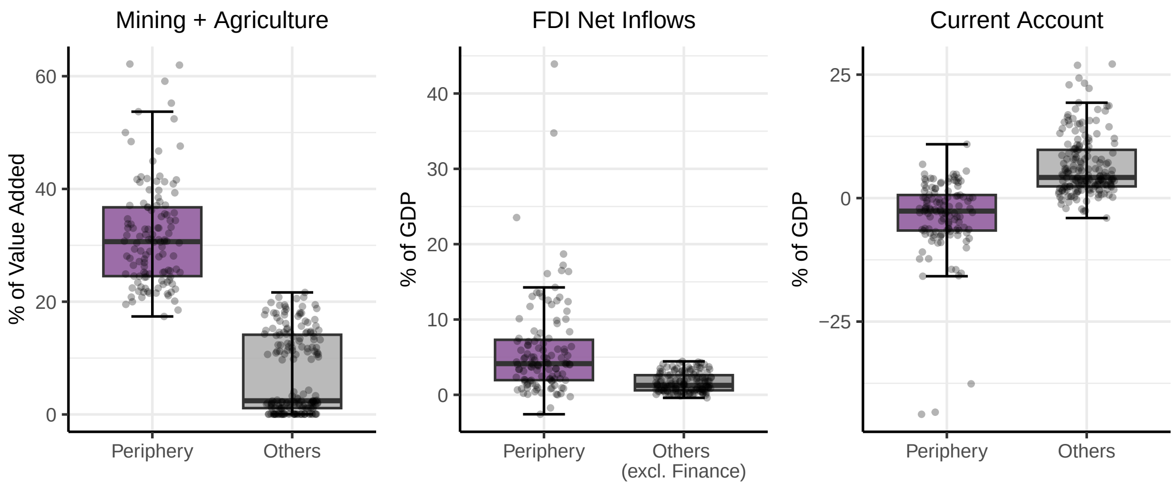
Figure 7: Cluster characteristics: a) Developmental States, b) Emerging Economies, c) Finance, d) Periphery.

Some further metrics can be put forward that help to illustrate structural differences

(c) Finance Hubs Characteristics



(d) Periphery Characteristics



(continued)

between the development models. The boxplots in Fig. 7 compare selected socio-economic indicators across clusters for the period 2000-2019, revealing how the four development trajectories relate to the developmental state blueprint outlined in Section 2.

The developmental states Japan, South Korea, and Taiwan exhibit characteristics consistent with their historical trajectory of state-led industrialization (see panel (a) of Fig. 7. Beyond the high economic complexity and income levels shown above, these economies display notably low FDI inflows compared to other clusters, reflecting the legacy of controlled financial systems that channeled domestic savings into strategic industries rather than relying on foreign capital (Haggard 2018; Studwell 2014). Income inequality remains comparatively low in South Korea and Taiwan, reflecting the path-dependent effects of comprehensive land reforms implemented in the 1950s-70s (Studwell 2014), whose egalitarian legacy persists in our 2000-2019 data. Japan represents an exception, exhibiting inequality levels comparable to emerging economies – likely related to prolonged stagnation and demographic pressures.

Notably, all three developmental states rank highest on the Liberal Democracy Index, substantially exceeding other East Asian economies.[9] As discussed in Section 2, the developmental states are characterized by a powerful bureaucratic apparatus exerting substantial discretionary power over private actors to discipline and direct them. Their authoritarian (or soft-authoritarian) origins were arguably essential to their effectiveness in disciplining businesses, managing financial flows, and guiding markets towards developmental objectives. Nevertheless, Japan, South Korea, and Taiwan are today the most democratic countries in the sample. Amsden (1989) argues that this might not be a contradiction. In South Korea, for example, the developmental state's success and the associated upgrading of human capital and establishment of large-scale factories may have "furthered political mobilization," (Amsden 1989, p.327) laying the groundwork for the democracy movement.

Against the theoretical background articulated in this study, the emerging economies – Malaysia, Thailand, the Philippines, and China – can be interpreted as incomplete implementations of the developmental state model (see panel (b) of Fig. 7. As Studwell (2014) documents, these countries adopted industrial policies but omitted crucial elements. Most notably, the absence of land reform in the 1950s-70s continues to manifest in

[9]The Liberal Democracy Index is included in Fig. 7 to illustrate variations in political institutions across the sample, particularly contrasting developmental states with other East Asian economies. Since this study identifies economically defined development models, purely institutional indicators are excluded from the main classification. The index accounts for aspects of a liberal understanding of democracy – protection of individual and minority rights, rule of law, independent judiciary, and checks and balances – taking a "negative" view of power focused on limits to government reach (Coppedge et al. 2025). Critically, this narrow view ignores democracy's conceptual contestability (Wolff 2023), which may be particularly relevant in non-Western contexts. Considering this measure in clustering does not substantially alter results: only Mongolia and Indonesia shift from periphery to emerging economies.

persistently high income inequality today, substantially exceeding the levels in South Korea and Taiwan. Without redistributive land reform, productive assets and income remained concentrated among elites, limiting the broad-based purchasing power that characterized developmental states.

These economies also show higher FDI inflows than developmental states, suggesting weaker financial controls and greater reliance on foreign capital. Primary sector activities – mining and agriculture combined – remain substantially more important than in developmental states, indicating incomplete structural transformation toward high-value manufacturing. These structural differences result in the intermediate positions on complexity and income observed earlier, distinguishing this cluster from both the fully transformed developmental states and the resource-dependent periphery.

The financial hubs Hong Kong and Singapore represent a fundamentally different pathway (see panel (c) of Fig. 7). Their financial sectors dominate economic activity at more than double the share observed in developmental states, while manufacturing plays only a minor role. These city-states exhibit massive bidirectional capital flows with exceptionally high FDI ratios and volatility. As trade intermediaries, their export ratios far exceed those of manufacturing-oriented developmental states. This finance-oriented model generates high prosperity but under very specific conditions – small size, strategic location, colonial commercial infrastructure – and serves as a local attractor for foreign corporations, financial firms and multinationals, making it difficult to replicate.

The peripheral economies – Cambodia, Laos, Myanmar, Indonesia, Mongolia, and Vietnam – remain primarily dependent on primary sectors (see panel (d) of Fig. 7). Mining and agriculture combined account for roughly a third of GDP, vastly exceeding all other clusters. This dominance in resource extraction and basic agriculture coincides with the negative complexity scores shown in Fig. 6, where negative values indicate below-average technological sophistication relative to global standards. These economies show higher FDI inflows than developmental states, reflecting dependence on external capital for any modern sector development. Current account balances vary considerably across countries and over time, though the cluster as a whole tends toward deficits. While developmental states deliberately "got prices wrong" (Amsden 1989) to enable industrial upgrading, peripheral economies have largely followed production patterns consistent with comparative advantages in primary commodities.

These structural differences illustrate that the developmental state model, while remarkably successful in Northeast Asia, represents only one pathway among several in East Asia. The clusters differ systematically in how they departed from or failed to implement the developmental state blueprint, with path-dependent legacies continuing to shape economic structures decades after initial policy choices.

4.4 Stability of the Cluster Classification

Having established the four development models and characterized their distinct economic features, this section examines the robustness and temporal stability of these classifications. We assess whether the identified country groupings remain stable over time and across alternative variable specifications, comparing cluster assignments based on rolling time windows and systematically varying the set of socio-economic input dimensions.

Given that East Asia is one of the world's most dynamic regions in terms of economic development, reflected in the high average growth rates across the country sample, it is especially useful to reintroduce the time-dimension, which is otherwise abstracted from in basing the clustering on static country-level fixed effects. By selecting time windows within the period of investigation 2000-2019, this approach allows for the identification of trends or structural breaks that occur over time in the classification of countries.

To this end, the period 2000-2019 has been divided into six overlapping five-year intervals, representing a rolling time window over the study period. The results show that cluster affiliations remain completely stable over time at this level of temporal resolution – no country changes its cluster membership across any of the five-year windows. While five-year periods are arguably short for structural classifications, this stability differs from Dominy et al. (2025), who find some cluster movements in European economies using even ten-year rolling windows. In our application, only when the length of the time intervals is further reduced, some volatility in cluster memberships can be observed. For example, when creating clusters for two-year periods, Indonesia switches from the periphery to the emerging economy group in several years, and Japan is sometimes clustered together with Hong Kong and Singapore. However, the changes in cluster membership do not follow a trend, but occur in an oscillating manner for both countries (as shown in Fig. A4 in the appendix). Moreover, the increase in volatility of country classification can be expected as shorter periods amplify the influence of year-specific outliers in the data, while longer intervals help to smooth out such effects through aggregation. Therefore, these very short periods may not offer robust results for identifying any structural trends or breaks, but merely accentuate cases at the boundaries between two clusters.

Similar to the result for cluster memberships over time, the country classification proves relatively robust to changes in the set of socio-economic dimensions used for clustering. Sankey diagrams are used to trace cluster memberships across alternative variable specifications, revealing which country groupings persist and which are sensitive to the choice of input dimensions. The Sankey diagram in Fig. 8 presents the four main clusters of Fig. 3 based on all 12 variables again, and compares them with results from alternative specifications using fewer dimensions.

To assess the robustness of our clustering results, we systematically test whether any single

Figure 8: Country clusters across different variable specifications

This figure compares cluster assignments across different sets of socio-economic variables. These variables are used to estimate the country-level fixed effect estimates that form the basis of the cluster assessment (see equation (3.1)). The clustering is performed using data from the complete study period 2000-2019.

variable dominates the classification. Excluding each of the 12 dimensions individually and re-estimating the country groupings yields identical four-cluster structures in all cases. This finding is particularly important for GDP per capita and the ECI, which receive the highest scaling factors (0.131 and 0.144 respectively) in the clustering algorithm. Furthermore, both variables potentially capture similar aspects of a country's development model, as the ECI is explicitly constructed to explain differences in income growth and predict divergent patterns of economic development (Hidalgo/Hausmann 2009; Hidalgo 2021), raising concerns about double counting.[10] However, our single exclusion tests demonstrate that neither variable alone drives the clustering, suggesting that double counting is not problematic in our specification.

Beyond testing individual variable exclusions, we also examine the effect of removing all four inherently interdependent sector shares of gross value added, namely financial and insurance activities, manufacturing, mining and quarrying, as well as agriculture, forestry and fishing. These sectoral variables also reflect development-related structural transformation, potentially contributing to the same concern about overweighting development dimensions in the clustering algorithm. Removing all sector shares results in only Indonesia shifting from the periphery to the emerging economies group.

[10]For that reason Dominy et al. (2025) consider only GDP per capita as an input dimension for their clustering of country characteristics in Europe, rather than both GDP and ECI.

To provide the most stringent test of potential development dimension overweighting, we examine what happens when both ECI and all sector shares are excluded simultaneously, leaving GDP per capita as the sole development-related indicator. Under this specification, the overall four-cluster structure remains intact and all other country assignments stay stable, with only Indonesia and Mongolia shifting from the periphery to the emerging economies group. While this sensitivity indicates that Indonesia and Mongolia occupy boundary positions between development models, it simultaneously highlights the value of including multiple development measures: Mongolia ranks very low in terms of economic complexity, a metric which the Philippines has managed to climb in recent years (see Fig. 6). Yet, Mongolia's average per capita income in 2021 was roughly 60% higher than that of the Philippines, making it the highest-income country in the periphery group, despite its low complexity, mining-oriented economy. Similarly, Indonesia's sectoral composition – characterized by high mining and low financial services shares – distinguishes it from typical emerging economies despite comparable GDP levels. These structural differences, captured by ECI and sector variables, provide crucial information for distinguishing development trajectories that income measures alone cannot reveal.

5 Conclusion

This study set out to answer the question, how the variety of development models observed among East Asian economies today can be categorized and conceptualized. Using a hierarchical clustering approach based on country-level characteristics across 12 socio-economic dimensions for the period 2000-2019 (FE clustering), four distinct development models were identified: the developmental states Japan, South Korea, and Taiwan; the finance group comprising the two city-states of Hong Kong and Singapore; the Southeast Asian economies of Malaysia, Thailand, and the Philippines classified together with China to form the emerging economies group; and East Asia's periphery, consisting of Indonesia, Vietnam, Mongolia, Myanmar, Laos, and Cambodia.

These country classifications align well with the theoretical framework established in Section 2, and are empirically intuitive: *Developmental* states are characterized by high levels of economic complexity and a significant share of value added generation in manufacturing, reflecting the legacies of state-led industrialization, deliberately "getting relative prices wrong" to promote technological upgrading (Amsden 1989, p.139). *Financial hubs* are distinguished by large FDI in- and outflows and a dominant financial and insurance sector, reflecting the dynamics of offshore finance and global capital flows. *Emerging economies* follow the principal trajectory of developmental states, but do not (yet) reach similar levels of income or technological sophistication, which could be due to a later, partial or distinct implementation of the guiding principles of the developmental state model. Eventually, *peripheral countries* share a focus on the primary sector, which structurally distinguishes their economies from the rest of the sample.

While the classification of East Asian countries in this paper proofs extremely robust — especially with regard to variations in terms of employed variables or the time-span analyzed — a challenge for the results also lies in accounting for China and Vietnam. The fact that both countries are nominally socialist, one-party states with strong state-led economic development strategies (Ang 2016; Studwell 2014; I. M. Weber 2021) does not seem especially problematic in our context as they are nonetheless embedded in a global regime of liberalized trade and finance. This integration has a strong imprint on both, which development strategies are conceived as politically feasible as well as which development models will eventually materialize in a given country. However, the categorization of these economics as emerging or even peripheral economies, does not seem to align too well with the strong technological dynamism often associated with both countries.

For Vietnam we observe rapid industrialization and export upgrading in recent decades, while other structural features – such as income levels, inequality, sectoral composition, and the depth of domestic financial and innovation systems – still align more closely with peripheral economies. This suggests that the common perception of Vietnam as an emerging economy may overemphasize its export success, whereas in a multidimensional structural sense, its development model still shares key features with the periphery. The categorization of China on the other hand likely reflects the country's extreme regional heterogeneity rather than a distinct national model. If China's provinces were analyzed separately, they might occupy nearly all positions in the multidimensional space – from highly financialized coastal regions resembling Hong Kong or Singapore to manufacturing-oriented hubs comparable to South Korea, and agricultural inland provinces closer to the periphery. The aggregate classification of China as part of the "emerging economy" cluster may thus reflect a statistical convergence-to-the-mean effect resulting from averaging over these diverse regional trajectories.[11]

Beyond documenting East Asia's economic heterogeneity, this study makes two contributions to development research. First, methodologically, we demonstrate that multidimensional cluster analysis based on country-level fixed effects can identify structurally distinct development trajectories within a region traditionally understood through a single dominant framework. While the developmental state literature has provided crucial insights into industrialization in North-East Asia, our results reveal that this model represents one pathway among four possible trajectories characterized by differences in global economic integration as well as domestic configurations. Second, theoretically, we show that even within a relatively cohesive geographic region, development models exhibit strong path dependence and stability over time, suggesting that successful strategies are not easily replicable across countries despite geographic proximity and shared cultural contexts. These findings caution against universalizing lessons from any single case and highlight the need for development research to engage systematically with structural diversity within regions.

Finally, when comparing our cluster results for East Asia with existing research on development models across European countries (Gräbner-Radkowitsch 2022; Dominy et al. 2025), we find some noteworthy similarities: *Developmental states* share the high income and technological sophistication of European *core countries*, where both areas have developed structurally distinct *financial hubs*, which also high income, while being much less dependent on industrial outputs. The emerging economies in East Asia structurally resemble the *workbench economies* in Eastern Europe, with the key difference that the latter are strongly tied to core countries, which is not consistently the case in East Asia. The strongest difference in this comparison concerns the *peripheral countries*, which are characterized by a focus on primary sectors in East Asia, while the in Europe this group suffers most strongly from prevalent deindustrialization and an associated decline in international market shares.

[11]We thank Yves Tiberghien for this insightful comment

These similarities across regions indicate the possibility that there is some degree of synchronization of the development models across different regions, where core factors of success and deprivation are shared among countries in different regions. Such a pattern is plausible against the backdrop of intensified global economic integration that also facilitates competition between nation states (Palan 2002; Rodrik 2011) with different development models. Hence, it seems plausible that such competitive pressures create winners and losers over time that share certain structural characteristics quite independent of their exact geographical location.

Future research may also benefit from incorporating subnational data, which would allow for the identification of within-country heterogeneity and reveal the internal diversity of development models, particularly in large economies such as China and Indonesia. The aggregation of data at the country level risks obscuring regional disparities, a challenge formulated by Gräbner/Kapeller (2024, p.64) as the "challenge of granularity," in the context of clustering European economies (Gräbner et al. 2020b).

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A Appendix

A.1 Technical Notes

A.1.1 Determining the Number of Clusters

Comparing Merger Heights Fig. A1 visualizes the heights at which every merging step in the agglomerative nesting of countries to cluster groups takes place (reading the figure from right to left, from 15 single-unit clusters to an individual cluster encompassing all countries). The point where the number of groups equals four is also the point at which the heights between successive mergers start to flatten out as cluster solutions with significantly more country groups are not very far away in terms of the height measure used in the dendrogram. The chosen solution with four country groups is thus like the elbow of a bent arm, marking a "jump" in the height change between successive clusters.

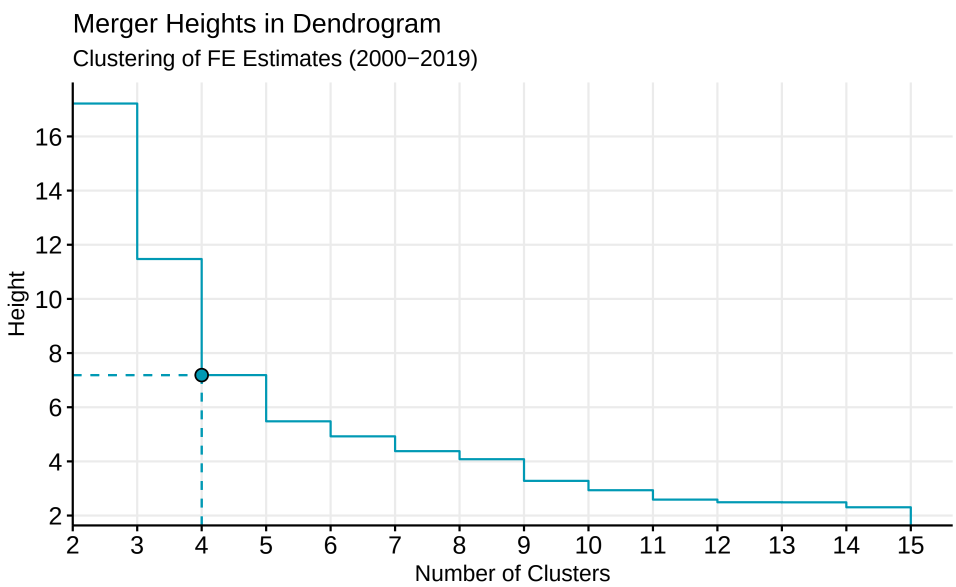

Figure A1: Merger heights

Comparing Within-Cluster Dispersion Another "elbow" metric referred to often by the literature refers to the idea of evaluating the change in the within-cluster dispersion for different numbers of clusters while considering the trade-off between bias and variance at the same time (Tibshirani et al. 2001). Smaller clusters with fewer countries enable less intra-cluster variation, so the function is decreasing monotonically as the number of clusters increases. However the gain in total compactness across all clusters, reducing the total within sum of squares of the cluster solution, usually levels off at some point. This point where the decrease becomes markedly smaller with the increase in the number of groups presents itself as an "elbow" in the plot. This is illustrated in Fig. A2. The visual examination of the elbow plot suggests a cluster solution with three, possibly four country groups. As can be seen in the dendrogram, three clusters would result in a merger of cluster 2 (red) and cluster 4 (green), creating a somewhat mixed group of seven emerging and industrialized economies.

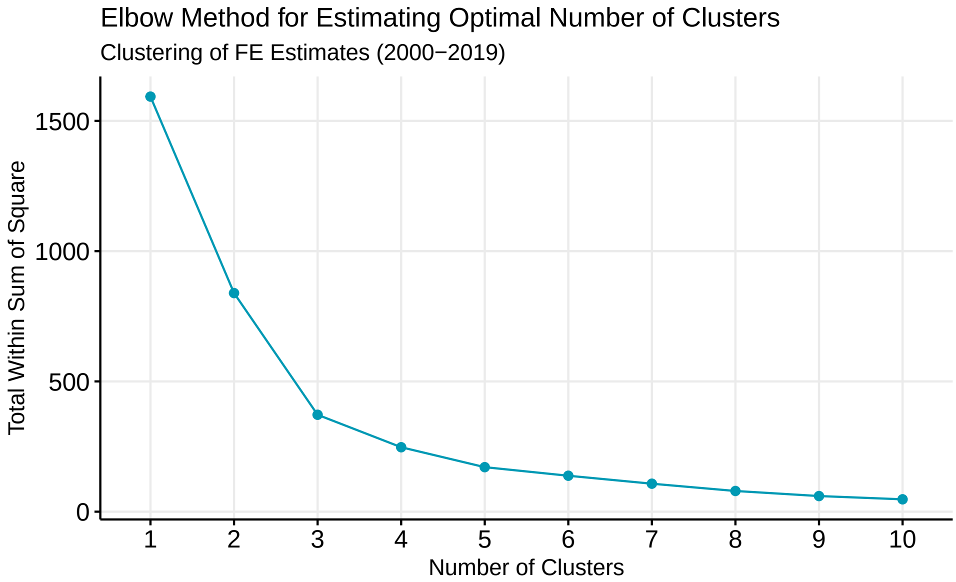

Figure A2: Elbow plot

Gap Statistic A formalization of the "elbow" intuition is presented by Tibshirani et al. (2001) in the form of the gap statistic (Everitt et al. 2011). Fig. A3 shows the gap statistic for the results of the FE clustering and provides more formal details on the measure. The idea of the gap statistic is to compare the total intra-cluster variation in the solution based on the actual data to that of modified, simulated datasets that conform to the dimensions of the original data but are devoid of any cluster structures. Specifically, the gap statistic uses the difference between the log of the total intra-cluster variation $log[C(n, g)]$ of the cluster solution with n units and g groups and its expected value from the null-references $E_n^*\{\log[C(n, g)]\}$:

$$GAP_n(g) = E_n^*\{\log[C(n, g)]\} - log[C(n, g)]$$

The size of the "gap" indicates how much better the chosen solution with g groups is compared to the clustering of the random noise in the simulated reference datasets. In this figure, the optimal number of clusters ($g = 4$) is then chosen according to the rule `firstSEmax`, which is the default option in the `clustGap()` command of the `cluster` package in R. This method takes the standard errors of the null-reference solutions into account and searches for the smallest g (thus avoiding over-fitting) that is not more than one standard error away from the first local maximum. The equation above defining the gap statistic is taken from Everitt et al. (2011).

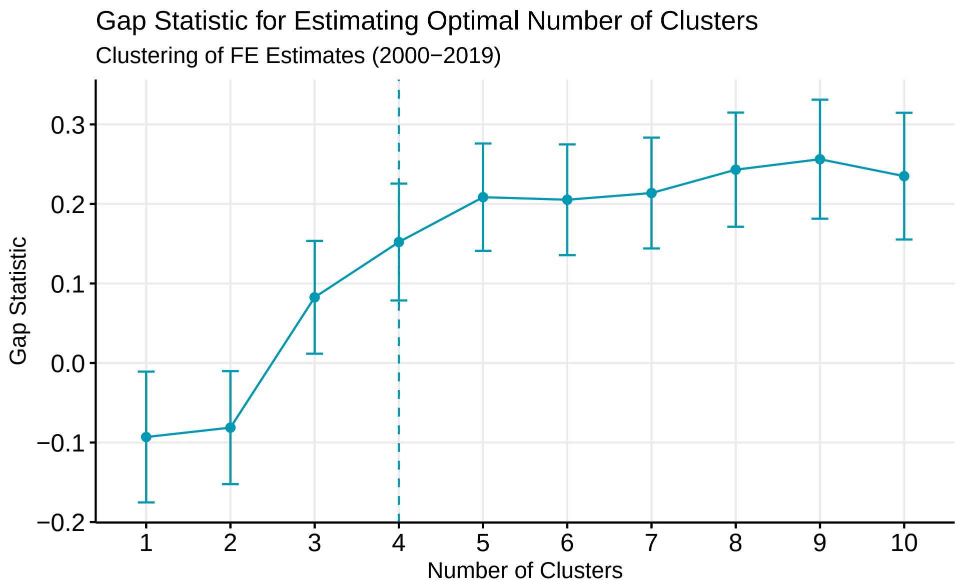

Figure A3: Gap statistic

A.1.2 Quality Assessment: Stress Measures

To evaluate the quality of the two-dimensional projection, we calculate two complementary stress measures. The key difference between them lies in what they assess: **Kruskal's stress** evaluates whether the *rank ordering* of distances is preserved (i.e., are closer countries still closer in the 2D map?), while **metric stress** measures whether the *absolute distance values* are preserved. By reporting both, we can assess whether the visualization accurately captures the ordinal structure of country relationships (most important for interpreting cluster configurations) and quantify the inevitable compression of distance magnitudes that results from dimensionality reduction.

Kruskal's Nonmetric Stress Kruskal's stress (Kruskal 1964) evaluates how well the rank ordering of distances is preserved:

$$\text{Stress}_{\text{Kruskal}} = \sqrt{\frac{\sum_{i<j}(d_{ij} - \hat{d}_{ij})^2}{\sum_{i<j} d_{ij}^2}}$$

where d_{ij} are the Euclidean distances in the 2D MDS space and $\hat{d}_{ij}$ are obtained through isotonic regression using the Pool Adjacent Violators Algorithm. This algorithm finds the values $\hat{d}_{ij}$ that are (1) monotonically related to the original distances δ_{ij} and (2) as close as possible to the MDS distances d_{ij}. Thus, Kruskal's stress measures deviations from the optimal monotone relationship, focusing on whether the ordinal structure is preserved rather than exact distance values.

Our analysis achieves $\text{Stress}_{\text{Kruskal}} = 8.6\%$. Following Kruskal's guidelines (0–5%: excellent;

5–10%: good; 10–20%: fair; >20%: poor), this indicates good preservation of similarity rankings. Practically, this means that when countries are more similar in the 12-dimensional economic space, they reliably appear closer in the 2D visualization, and vice versa. The low stress value confirms that the spatial arrangement of countries in the factor map accurately reflects their structural economic relationships.

Metric Stress Metric stress directly measures Euclidean distance deviations without allowing monotone transformation:

$$\text{Stress}_{\text{metric}} = \sqrt{\frac{\sum_{i<j}(d_{ij} - \delta_{ij})^2}{\sum_{i<j}\delta_{ij}^2}}$$

This yields 19%, indicating that absolute distance values deviate on average by 19% from the original weighted distances. This higher value compared to Kruskal's stress reflects that while the rank ordering is well preserved (8.6%), absolute distance magnitudes are necessarily compressed in the low-dimensional projection—an expected consequence of reducing dimensionality from 12 to 2 (83% reduction).

The difference between these measures demonstrates that the factor map reliably captures the ordinal structure of country similarities, making it suitable for visualizing cluster relationships, though precise distance ratios should be interpreted with appropriate caution.

A.2 Additional Tables

Table A1: Variables and comments on data sources

Variable	Source	Comments
Public debt (% of GDP)	Global Debt Database, IMF (Mbaye et al. 2018)	Data covers general government debt for all countries, except Laos, Myanmar, Hong Kong, and Singapore for which only central government debt is available
Exports of goods and services (% of GDP)	World Development Indicators, World Bank	Data for Taiwan is from the National Statistics of Taiwan, data for Myanmar from the World Integrated Trade Solution database
GDP p.c. (deviation from sample mean)	IMF World Economic Outlook, October 2024	Own calculation, GDP per capita data is in constant 2017 international dollars at purchasing power parity

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Table A1 – continued from previous page

Variable	Source	Comments
Unemployment rate	World Development Indicators, World Bank	Data for Taiwan is from the IMF World Economic Outlook
Current account balance (% of GDP)	World Development Indicators, World Bank	Data for Taiwan is from the IMF World Economic Outlook
Share of financial & insurance activities in total gross value added	Compiled from various sources	Own calculation of shares based on data sources, see Table A3 for the list of sources used for each country
Share of manufacturing in total gross value added	Compiled from various sources	Own calculation of shares based on data sources, see Table A3 for the list of sources used for each country
Share of agriculture, forestry and fishing in total gross value added	Compiled from various sources	Own calculation of shares based on data sources, see Table A3 for the list of sources used for each country
Share of mining & quarrying in total gross value added	Compiled from various sources	Own calculation of shares based on data sources, see Table A3 for the list of sources used for each country
Gini on market income	Standardized World Income Inequality Database (Solt 2022)	
FDI inflows (% of GDP)	UN Trade and Development (UNCTAD)	Inflows net of reverse investment
Economic Complexity Index	The Atlas of Economic Complexity	Index based on the SITC product classification
Liberal Democracy Index	V-Dem Varieties of Democracy	

Source Name	Abbreviation
OECD National Accounts at a Glance, chapter 4: Production	OECD NAAG
OECD TiVA, Trade in Value Added	OECD TiVA
Asian Development Bank, Gross Value Added at Current Prices	ADB
UN National Accounts Estimates of Main Aggregates, Gross Value Added by Kind of Economic Activity at Current Prices (National Currency)	UN NA Estimates
UN National Accounts Official Country Data, Table 2.4 Value Added by Industries at Current Prices (ISIC Rev. 4)	UN NA Official Country Data
National Statistics, Republic of China (Taiwan), Gross Domestic Product by Kind of Activity	Taiwan National Statistics
National Bureau of Statistics China, Value Added by Industries	China National Statistics

Table A2: Data sources for industry shares in total gross value added

Table A3: Sources for industry shares in total gross value added, for each country

Country	Industry Share in Total Gross Value Added	Source
China	Financial & insurance activities	OECD NAAG
	Manufacturing	OECD TiVA
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	China National Statistics
Hong Kong	Financial & insurance activities	ADB
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Indonesia	Financial & insurance activities	OECD TiVA
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Japan	Financial & insurance activities	OECD NAAG
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Cambodia	Financial & insurance activities	ADB
	Manufacturing	UN NA Estimates

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Table A3 – continued from previous page

Country	Industry Share in Total Gross Value Added	Source
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
South Korea	Financial & insurance activities	UN NA Official Country Data
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Laos	Financial & insurance activities	ADB
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Myanmar	Financial & insurance activities	OECD TiVA
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Mongolia	Financial & insurance activities	UN NA Official Country Data
	Manufacturing	UN NA Estimates
	Mining & quarrying	UN NA Official Country Data
	Agriculture, forestry and fishing	UN NA Estimates
Malaysia	Financial & insurance activities	OECD TiVA
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Philippines	Financial & insurance activities	UN NA Official Country Data
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Singapore	Financial & insurance activities	UN NA Official Country Data
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Thailand	Financial & insurance activities	UN NA Official Country Data
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates
Taiwan	Financial & insurance activities	ADB

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Table A3 – continued from previous page

Country	Industry Share in Total Gross Value Added	Source
	Manufacturing	Taiwan National Statistics
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	Taiwan National Statistics
Vietnam	Financial & insurance activities	OECD TiVA
	Manufacturing	UN NA Estimates
	Mining & quarrying	OECD TiVA
	Agriculture, forestry and fishing	UN NA Estimates

Variable	MDS Dimension 1	MDS Dimension 2
GDP p.c. (dev.)	-0.91	0.10
Agriculture	0.90	0.13
Finance Share	-0.86	0.42
ECI	-0.86	-0.47
Current Account	-0.85	-0.12
Mining	0.55	0.33
Inequality (Gini)	-0.49	0.17
FDI Inflows	-0.42	0.85
Manufacturing	-0.15	-0.81
Public Debt	-0.14	-0.34

Table A4: Variable loadings on MDS dimensions

Pearson correlation coefficients between country-level fixed effects and MDS coordinates, sorted by absolute correlation strength with MDS Dimension 1. Vector length in Fig. 4 corresponds to these correlation values scaled by factor 4 for visibility.

A.3 Cluster Memberships over Time

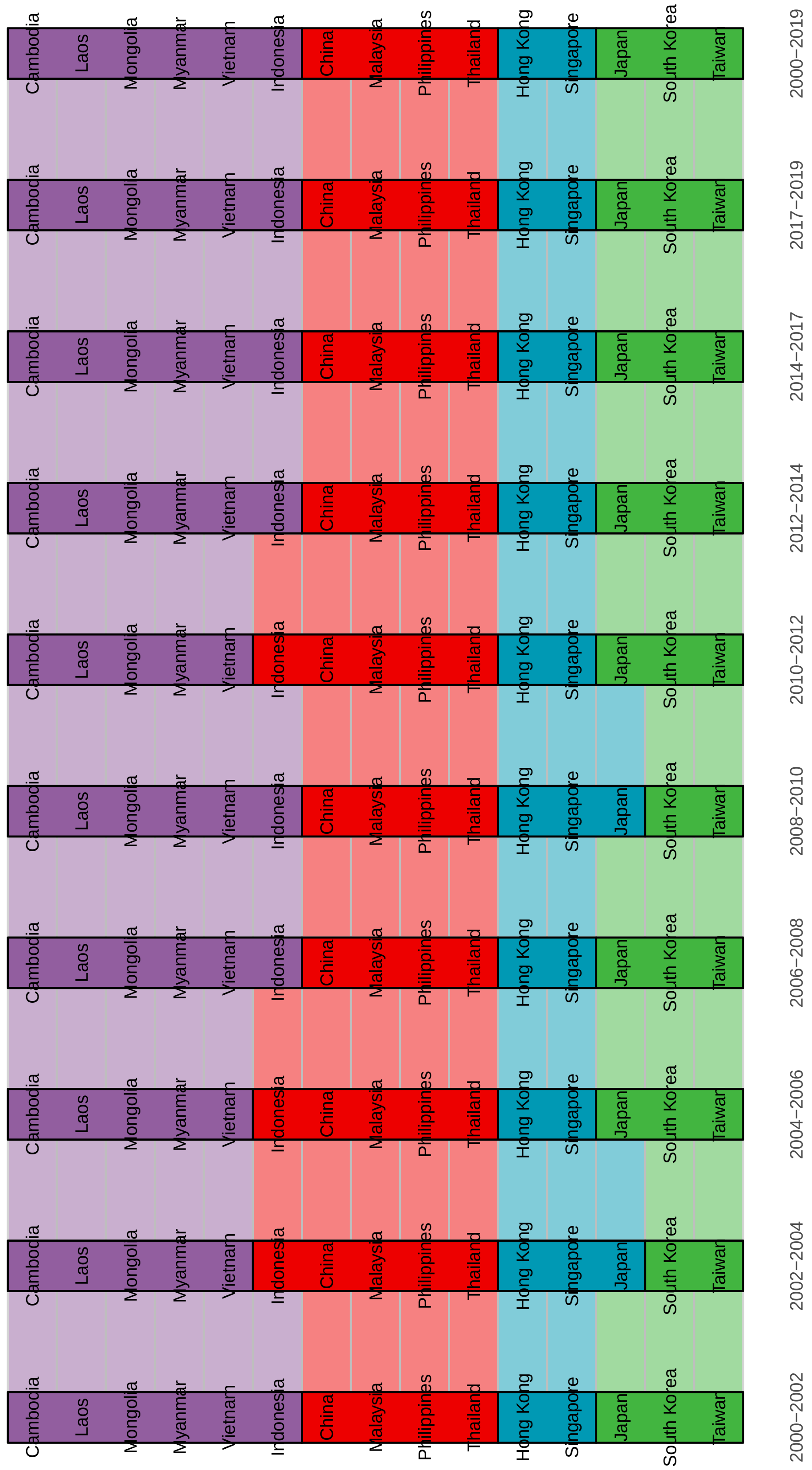

Figure A4: Cluster memberships over time (two year-intervals)

This figure presents the classification results over two-year intervals between 2000 and 2019. Colors correspond to the groups in Fig. 3. Despite the short interval length, which increases sensitivity to outliers, cluster memberships remain largely stable over time. Exceptions are Indonesia, and Japan, which shift between clusters in several periods.

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