Diagnosing Barriers to Technological Catch-Up: Evidence from a Hierarchical Bayesian Model of OECD Economies

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Abstract

This thesis develops a hierarchical Bayesian model to estimate technological absorption across 37 OECD countries (2000–2021) along two dimensions: exposure to frontier knowledge (Direct Absorption Index, DAI) and internal conversion frictions (Catch-Up Friction Index, CUFI). The model nests countries within regional–income groupings and embeds a translog production system with feedback between output and human capital. The empirical estimates reveal striking cross-country contrasts. Switzerland, the United States, and the United Kingdom lead in both absorption and friction reduction. On the other hand, Japan and South Korea lag due to factors such as domestic technological resistance despite their technological reputation. Latvia, Lithuania, and Costa Rica rank lowest and face deficits across both indices. These patterns suggest that absorptive capacity is shaped not merely by technological potential but by institutional and structural characteristics. The framework offers a policy-relevant diagnostic tool for identifying bottlenecks and designing targeted interventions to support sustained productivity convergence.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Chapter 1 – Introduction

Technological progress has long been regarded as a key driver of economic growth, productivity, and structural transformation. Foundational models of economic growth, such as Solow's (1957) exogenous framework and Romer's (1990) endogenous growth theory, highlight the pivotal role of technological change in sustaining long-run output growth. While these models differ in how they explain the source of innovation, both converge on the central importance of technology in driving increases in output per worker and shaping macroeconomic trajectories. In particular, Romer (1990) emphasises the non-rival nature of ideas, their ability to be reused indefinitely at near-zero marginal replication cost. This property underpins endogenous growth by allowing continuous capital accumulation without the diminishing returns characteristic of rivalrous inputs.

Despite the widespread recognition of technology as a key driver of growth, it remains unclear why some advanced economies are better able to absorb and benefit from global innovation than others. Among OECD countries, where access to cutting-edge technologies is relatively high, this uncertainty is especially striking. A growing body of empirical work suggests that the translation of technological inputs into economic gains varies substantially. For instance, evidence from energy-growth studies shows that while some OECD countries effectively leverage renewable energy to enhance output, others exhibit limited or insignificant returns (Chontanawat et al., 2008; Gozgor et al., 2018; Ivanovski et al., 2021). These disparities point to deeper structural, institutional, or regional frictions that mediate the process of technological absorption.

The urgency of this investigation has intensified in recent decades, as the global innovation landscape has undergone a profound transformation. Digital technologies and the rise of the internet have dramatically accelerated the cross-border diffusion of knowledge and innovation. Box and West (2016) highlight how digital connectivity has eroded many of the geographic, linguistic, and institutional barriers that once constrained the exchange of tacit knowledge. As a result, countries today enjoy faster and broader access to technological advancements than at any point in history.

Krzakiewicz and Bartkowiak (2021) document this acceleration, noting that global imitation lags have fallen from around 100 years in the early 19th century to as little as 12 to 18 months by the 1980s. Yet despite these significant reductions in diffusion time, convergence in productivity and technological capacity remains incomplete and uneven. Koc and Teker (2019) observe that countries with strong absorptive capabilities have surged ahead, while others continue to lag. If access to technology is increasingly global, what accounts for the persistent heterogeneity in its economic impact?

To move beyond descriptive institutional analysis, this study quantifies technological absorption as a dynamic, hierarchical process, capturing both cross-country heterogeneity and the frictions that inhibit the translation of innovation into productivity. The framework distinguishes between two critical barriers to convergence: (a) Direct Absorption, reflecting a country's exposure to frontier technologies, and (b) Catch-Up Friction, capturing domestic constraints that hinder the internalisation and productivity-enhancing use of external innovations. While theory has long emphasised diffusion's role in economic development (Abramovitz, 1986; Schumpeter, 1939), empirical models rarely disentangle access to global innovations from the capacity to exploit them. This study addresses that gap by decomposing technological absorption into measurable components that reflect both exposure and internal conversion.

This distinction builds on a rich theoretical foundation that has long recognised the importance of diffusion, imitation, and catch-up in shaping growth trajectories. Schumpeter (1939) emphasised that innovation begets imitation, initiating processes of creative destruction. Mansfield (1961) formalised how perceived risks and peer adoption affect the pace of diffusion, while Abramovitz (1986) introduced the notion of "social capability" to capture a country's readiness to harness external technologies. Empirical work by Sala-i-Martin and Barro (1995) further demonstrated that imitation is typically less costly than innovation, though its success hinges on supportive domestic conditions. Nelson and Wright (1992) attributed post-war convergence to growing international openness, mobile labour, and the rise of transnational innovation networks. Yet despite these insights, few empirical frameworks operationalise these concepts in a dynamic, multilevel structure capable of parsing the distinct roles of exposure and internal absorption.

This study addresses a key empirical gap by introducing a hierarchical framework that models technological dynamics through three core components: (1) the global technological frontier; (2) a Direct Absorption Index (DAI), capturing a country's effectiveness in internalising external technologies; and (3) a Catch-Up Friction Index (CUFI), reflecting domestic constraints that hinder diffusion. The model is estimated in a Bayesian setting using panel data from 37 OECD countries (2000–2021), enabling flexible inference across countries, regions, and income groups. The hierarchical structure captures unobserved heterogeneity while borrowing strength across related units, offering a more refined picture of absorptive capacity. This multilevel design extends earlier typologies, such as Fagerberg's (1987) productivity–technology clusters, by providing a dynamic, data-driven decomposition of technological performance.

This framework advances the literature in three key ways. First, it operationalises core theoretical constructs, from Schumpeterian diffusion to Abramovitz's social capability, within a unified statistical model. Second, it empirically separates exposure to innovation (DAI) from internal conversion efficiency (CUFI), enabling a clearer diagnosis of where and why technological divergence persists. Third, it tracks how these components evolve over time, shedding light on both persistent structural bottlenecks and dynamic improvements. In doing so, the study offers practical, interpretable metrics for understanding the anatomy of technological progress and its implications for long-run economic transformation. These contributions set the stage for a more contextualised examination of prior empirical approaches, to which the next section now turns.

Chapter 2 – Literature Review

A substantial body of research has explored the forces driving cross-country economic convergence, with technological diffusion occupying a central position. Theoretical models have long distinguished between innovation, through which frontier economies develop new technologies, and imitation, which allows lagging nations to catch up. Schumpeter (1939) introduced the idea of innovation waves disrupting economic equilibrium, while Mansfield (1961) formalised how risk and uncertainty shape diffusion lags. Abramovitz (1986) added that a nation's capacity to benefit from diffusion depends on its "social capability", institutional and structural readiness for absorbing new knowledge. Fagerberg (1987) operationalised these insights by classifying countries into static technology and productivity groups to explain growth differentials.

Empirical studies have supported these foundational claims. Abramovitz (1986) attributed post-war convergence in OECD countries to expanding international knowledge flows and rising capital mobility. Sala-i-Martin and Barro (1995) demonstrated that imitation is a relatively inexpensive growth pathway if institutional capacity exists. Nelson and Wright (1992) emphasised the importance of openness and labour mobility in driving convergence. More recently, Bloom et al. (2004), Bucci et al. (2019), and Swift (2011) have shown that human capital, particularly life expectancy, plays a vital role in enhancing long-run growth. Similarly, Perez-Trujillo and Lacalle-Calderon (2020) demonstrated that internet connectivity accelerates convergence by facilitating access to frontier technologies and lowering diffusion costs.

Parallel strands of research in energy economics also show that access alone does not guarantee convergence. Studies such as Chontanawat et al. (2008) and Gozgor et al. (2018) reveal that renewable energy adoption yields highly heterogeneous growth effects across OECD countries, despite similar energy transitions. Ivanovski et al. (2021) attribute this divergence to latent institutional constraints. Non-renewable energy sources tend to display stronger growth associations (Apergis & Payne, 2012; Bhattacharya et al., 2016), but even these links are mediated by structural factors such as energy intensity, capital accumulation, and sectoral integration (Apergis & Payne, 2010; Salim et al., 2014). These energy asymmetries characterise a core limitation in diffusion literature: they reveal institutional frictions (later quantified as CUFI) as the decisive factor, not exposure, in explaining heterogeneous returns.

Taken together, these studies offer a critical insight: convergence depends not only on access to global knowledge and technologies but also on a country's internal capacity to convert them into productivity. However, most empirical models remain limited in this regard. They often treat technological diffusion as a homogenous or black-box process, inferring convergence from observed output trends without explicitly modelling the intermediate steps of absorption. Thus, a core empirical gap persists while existing work has identified the conditions for convergence, few studies have developed a dynamic, multilevel framework that separates exposure to frontier technologies from internal conversion efficiency. Most approaches collapse the complex absorption process into static clusters or single-equation estimates, failing to explain why countries with similar access to innovation yield sharply different growth outcomes.

To address this gap, the following research question is proposed:

How can this study empirically disentangle the roles of global exposure and domestic conversion efficiency in shaping technological absorption and productivity convergence across advanced economies?

This study introduces a new empirical framework to answer this question. Building on the theoretical contributions of Schumpeter, Abramovitz, and Fagerberg, a dynamic Bayesian hierarchical model is proposed that decomposes technological absorption into two empirically measurable components:

a) Direct Absorption Index (DAI): capturing a country's exposure to frontier technologies via digital infrastructure, human capital, and openness to trade and investment.

b) Catch-Up Friction Index (CUFI): quantifying the domestic constraints such as institutional rigidity, policy inefficiencies, or labour market mismatches that inhibit the conversion of exposure into productivity.

Unlike Fagerberg's (1987) static technology gap-based clustering and aggregate convergence regressions, this dynamic decomposition isolates absorption mechanics at country, region, and income-group levels. This means the evolution and interaction of components can be tracked over time to capture persistent structural bottlenecks and dynamic improvements, rather than analysing a static environment. The use of Bayesian analysis over other methods also allows priors to be accounted for, resulting in more informed outputs.

This study contributes to the literature in several key ways. First, it operationalises longstanding theoretical constructs, such as Schumpeterian diffusion and Abramovitz's social capability, within a coherent and flexible statistical framework. Second, it provides granular diagnostics by empirically distinguishing between access (DAI) and internal frictions (CUFI), offering deeper insight into why countries diverge despite similar exposure. Third, it enables dynamic tracking over two decades, uncovering both persistent bottlenecks and structural improvements. These dynamics are explored in the empirical results, which highlight regional asymmetries (e.g., Nordic resilience, Southern volatility) and CUFI-driven divergence even where exposure is high.

Finally, the model delivers actionable insights for policymakers. Countries with low DAI may prioritise digital infrastructure, FDI liberalisation, or cross-border R&D partnerships to boost exposure. Countries with high CUFI may need institutional reform, workforce development, or better sectoral alignment to improve conversion efficiency. In sum, this study bridges a longstanding empirical and conceptual gap, offering both a theoretical lens and a practical diagnostic tool for understanding and addressing the persistent asymmetries of technological diffusion in the global economy.

Chapter 3 – Data & Descriptive Statistics

This study uses an unbalanced panel comprising 814 observations from 37 OECD countries over the 2000–2021 period (22 years). Slovenia was excluded due to excessive missing data. All variables are expressed in per capita or normalised terms to facilitate meaningful cross-country comparisons.

Table 1 presents descriptive statistics for the main variables. Real GDP per capita, measured in constant 2015 USD, was obtained from the World Bank's DataBank (The World Bank, 2023a). The values range from just over $4,000 to $112,000, reflecting substantial income heterogeneity across countries. The employed labour force, defined as individuals aged 15 and above who are actively employed (International Labour Organization, 2024), shows a narrow distribution, with a mean of 0.49 and a maximum of 0.59. Missing values for Costa Rica (2000) and Colombia (2006) were imputed using interpolated estimates.

Table 1
Summary Statistics

Variable	Measurement	Obs	Min.	1st Qu.	Median	Mean	3rd Qu.	Max
Real GDP	USD (per person)	814	4,011.66	14,504.91	34284.10	34,388.85	45,585.17	112,481.11
Employed Labour	Persons (per person)	814	0.19	0.45	0.50	0.49	0.52	0.59
Gross Fixed Assets	Index (per million persons)	814	0.25	1.98	9.22	24.82	17.59	560.31
Energy Consumption	MMBtu (per person)	814	23.03	98.33	140.22	154.00	205.90	436.82
Life Expectancy	Years	814	70.13	77.03	79.65	78.99	81.45	84.56
Population	Thousands of persons	814	281.20	5,319.38	10506.31	34,865.19	47,274.82	332,031.55

Gross fixed capital formation (GFCF) data, drawn from the OECD Data Explorer (OECD, 2024), are expressed as an index (2015 = 100) and reflect investment in both physical and intellectual capital. The variable displays strong right-skewness, with a few observations showing extremely high capital intensity. Total energy consumption, sourced from the U.S. Energy Information Administration (2023), is reported in MMBtu per capita and includes all major sources, renewables, fossil fuels, and nuclear energy. The wide dispersion in this variable (23 to 437 MMBtu) suggests cross-country differences in energy intensity and industrial structure.

Life expectancy at birth, measured in years and obtained from the World Bank DataBank (The World Bank, 2023b), averages approximately 79 years, with a relatively narrow interquartile range. This indicator serves as a proxy for human capital and institutional development. Population figures, reported in thousands and drawn from the OECD Data Explorer (OECD, 2023b), exhibit high variation, from small advanced economies with fewer than one million people to large countries with over 300 million, enabling conversion of all key indicators to per capita units.

Chapter 4 – Model Specification and Empirical Methodology

This study employs a translog production function – an extension of the traditional Cobb-Douglas model, allowing for variable elasticities of substitution among inputs. Unlike the Cobb-Douglas specification, which assumes constant elasticities and unitary substitution, the translog model accommodates a more flexible production structure, making it suitable for analysing multiple inputs with potentially varying elasticities (Christensen, Jorgenson, & Lau, 1973).

The empirical model that captures the relationship between real GDP per capita and its key determinants while accounting for regional heterogeneity, technological progress, and human capital can be expressed as[1]:

$$
\begin{aligned}
\ln Y_{it} = {} & \alpha_Y + \beta_{L,r} \ln L_{it} + \beta_{K,r} \ln K_{it} + \beta_{E,r} \ln E_{it} + \frac{1}{2}\gamma_{LL,r}(\ln L_{it})^2 + \frac{1}{2}\beta_{KK,r}(\ln K_{it})^2 \\
& + \frac{1}{2}\beta_{EE,r}(\ln E_{it})^2 + \beta_{LK,r} \ln L_{it} \,.\, \ln K_{it} + \beta_{LE,r} \ln L_{it} \,.\, \ln E_{it,r} + \beta_{KE,r} \ln K_{it} \,.\, \ln E_{it} \\
& + \gamma_{H\to Y,r} \ln H_{it} + \gamma_{H^*\to Y,r} \ln H_{i,t-1} + \gamma_{H^2\to Y,r} \ln H_{it}^2 + \alpha_{t,Y} + \phi_i^Y v_{Y,it-1} + v_{Y,it} + \tau_{it} \quad (1.)
\end{aligned}
$$

In this specification, $\ln Y_{it}$ represents the natural logarithm of real GDP per capita for i at time t, and $\ln L_{it}$, $\ln K_{it}$, and $\ln E_{it}$ are the natural logarithms of employed labour, gross fixed assets, and energy consumption, respectively, all measured on a per capita basis. The focus on per capita measures normalises population differences, enabling meaningful cross-country comparisons and emphasising individual-level productivity (Fulmer, 1950).

The region-specific elasticities $\beta_{L,r}$, $\beta_{K,r}$, $\beta_{E,r}$ reflects the percentage change in GDP per capita resulting from a 1% change in each input per capita. Similarly, the second-order terms $\beta_{LL,r}$, $\beta_{KK,r}$ and $\beta_{EE,r}$ and interaction terms $\beta_{LK,r}$, $\beta_{LE,r}$ and $\beta_{KE,r}$ are also region-specific and capture diminishing or increasing returns to scale, as well as input complementarities or substitutability.

[1] In this study, the arrows (→) in the notation denote elasticities or statistical relationships between variables and do not imply causality.

Following the works of Bloom et al. (2004) and Swift (2011), human capital is proxied by average life expectancy at birth, and its contributions to GDP are captured through the elasticities $\gamma_{H\to Y,r}$, $\gamma_{H^*\to Y,r}$ and $\gamma_{H^2\to Y,r}$. These parameters are region-specific and measure the contributions of current human capital ($\gamma_{H\to Y,r}$), lagged human capital ($\gamma_{H^*\to Y,r}$) and the square of human capital ($\gamma_{H^2\to Y,r}$) to real GDP per capita. The inclusion of the quadratic term, $\ln H_{it}^2$ reflects potential nonlinearities in the relationship between human capital and GDP, capturing diminishing or increasing returns to human capital investment, such as the saturation of benefits or the compounding effects of improved education and healthcare systems. The region-specific nature of these parameters allows for heterogeneity in the impacts of human capital, recognising the influence of contextual factors such as regional health systems, education quality, and demographic profiles.

The relationship between GDP and human capital is bidirectional, as illustrated by the following equation:

$$\ln H_{it} = \alpha_H + \gamma_{Y\to H,r} \ln Y_{it} + \gamma_{Y^*\to H,r} \ln Y_{i,t-1} + \gamma_{Y^2\to H,r} \ln Y_{it}^2 + \alpha_{t,H} + \phi_i^H v_{H,it-1} + v_{H,it} \quad (2.)$$

Here, $\ln H_{it}$ is the natural logarithm of human capital (proxied by life expectancy). The elasticities $\gamma_{Y\to H,r}, \gamma_{Y^*\to H,r}$ and $\gamma_{Y^2\to H,r}$ capture the influence of current and lagged GDP on human capital, while the quadratic term $\ln Y_{it}^2$ accounts for potential nonlinearities in this relationship. Once again, the inclusion of the quadratic term acknowledges that the benefits of GDP on human capital investments, such as in healthcare and education, may exhibit diminishing or compounding returns depending on a region's developmental stage. The inclusion of lagged values accounts for the time-lagged effects of health and education investments on economic performance (Ahmad & Khan, 2018; Tsai et al., 2010).

This specification recognises the bidirectional relationship between GDP and human capital. On one hand, higher GDP levels enable greater investment in healthcare, education, and infrastructure, thereby improving life expectancy. On the other hand, enhanced human capital contributes to economic growth by increasing productivity, facilitating knowledge diffusion, and fostering innovation. Swift (2011), in a study across 13 countries, empirically demonstrated this dynamic, showing that lagged GDP positively influenced life expectancy in most cases.

Although equations (1) and (2) represent a recursive structure, they are estimated jointly within a unified hierarchical Bayesian framework. Each equation is assigned a distinct Gaussian likelihood and estimated with its own set of region and income-group-specific parameters. While the model reflects the feedback loop between GDP and human capital, it does not rely on a sequential or two-stage estimation approach. Instead, both equations are fitted simultaneously within a coherent probabilistic structure, allowing parameter estimates to be informed by the data and the shared hierarchical priors. This joint estimation framework retains the interpretability of structural recursive relationships while rigorously accounting for parameter uncertainty and cross-equation dependencies arising from the hierarchical specification.

To ensure robustness, symmetric shocks ($v_{Y,it}$, $v_{H,it}$) in Eq. (1) and (2) are modelled using a Student's t distribution, $v_{Y,it} \sim Student\_t(\vartheta_Y, 0, \sigma_{Y_v})$ and $v_{H,it} \sim Student\_t(\vartheta_H, 0, \sigma_{H_v})$ which provides resilience against outliers (Geweke, 1993).

Equations (1) and (2) incorporate residual persistence through Moving Average terms, $\boldsymbol{\phi_Y} = [\phi_{Y_1}, \phi_{Y_2}, \dots, \phi_{Y_I}]$ and $\boldsymbol{\phi_H} = [\phi_{H_1}, \phi_{H_2}, \dots, \phi_{H_I}]$ to capture the lingering effects of unobserved shocks. These terms ensure that the model accounts for temporal dependencies and mitigates potential endogeneity from omitted variables or feedback loops between GDP and human capital. The Moving Average terms are modelled at the country-specific level to reflect the unique characteristics of each country's economic and social dynamics, ensuring that the persistence effects are tailored to the specific contexts of individual countries rather than generalised across regions.

The time effects for GDP and human capital equations are modelled jointly to account for shared global influences, such as macroeconomic shocks and demographic transitions, which simultaneously impact both variables. These effects are represented as a bivariate normal distribution, where the time-specific effects for GDP ($\alpha_{t,Y}$) and human capital ($\alpha_{t,H}$) are jointly distributed. This joint representation is expressed as:

$$\begin{bmatrix} \alpha_{t,Y} \\ \alpha_{t,H} \end{bmatrix} \sim Normal\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{\alpha_{t,Y}} & \theta \cdot \sigma_{\alpha_{t,Y}} \cdot \sigma_{\alpha_{t,H}} \\ \theta \cdot \sigma_{\alpha_{t,Y}} \cdot \sigma_{\alpha_{t,H}} & \sigma^2_{\alpha_{t,H}} \end{bmatrix} \right) \quad (3.)$$

This joint modelling of time effects acknowledges shared global trends, such as macroeconomic shocks and demographic transitions, which influence both GDP and human capital. By modelling the time effects in this way, the correlation (θ) between the two variables is explicitly captured and restricted to lie between -1 and 1. This ensures a realistic and valid representation of the interconnected nature of global influences on GDP and human capital.

As specified in Eq. (1), the model incorporates regional-specific differences in the elasticities of labour, capital, energy, and human capital through a hierarchical structure, where regional elasticities are nested within income-group classifications, such as advanced and emerging economies. This hierarchical design allows input elasticities for labour, capital, and energy to vary across regions while being informed by broader income-based trends, effectively capturing the layered economic diversity within OECD regions.

This methodology builds upon the work of Burke and Csereklyei (2016), where energy-GDP elasticities are estimated for 132 countries between 1960-2010. While a hierarchical approach is not used, elasticities are estimated through both regional and income-based groupings of countries (Burke & Csereklyei, 2016). By nesting regional elasticities within income-based classifications, the model provides a dual perspective: it allows for an understanding of how elasticities differ between advanced and emerging economies while also revealing how they vary within regions due to localised factors. This dual-level analysis offers a richer understanding of production dynamics than would be possible with a purely regional or income-based approach alone.

The hierarchical structure leverages the concept of "borrowing strength," wherein parameter estimates at the regional level are informed by broader income-group-level patterns, reflecting shared characteristics across regions within the same income group. This approach enables the model to achieve a balance between capturing the overarching economic distinctions of advanced and emerging economies and reflecting localised heterogeneity.

Starting from the income-specific elasticities for labour, capital and energy are modelled as deviations from the global baselines. The global elasticities, along with their second-order and interaction terms, are represented as $\boldsymbol{\beta_p} = [\beta_L, \beta_K, \beta_E, \beta_{LL}, \beta_{KK}, \beta_{EE}, \beta_{LK}, \beta_{LE}, \beta_{KE}]'$ and income-group-specific deviations from these global elasticities are captured in $\boldsymbol{\beta_{p,j}} = [\beta_{L,j}, \beta_{K,j}, \beta_{E,j}, \beta_{LL,j}, \beta_{KK,j}, \beta_{EE,j}, \beta_{LK,j}, \beta_{LE,j}, \beta_{KE,j}]'$, and modelled hierarchically as:

$$\boldsymbol{\beta_{p,j}} \sim Normal(\boldsymbol{\beta_p}, \boldsymbol{\sigma_p^j}) \quad (4.)$$

where $\boldsymbol{\sigma_p^j}$ denotes the standard deviation of deviations in the p-level parameters across income groups. Regional deviations, $\boldsymbol{\beta_{p,r}} = [\beta_{L,r}, \beta_{K,r}, \beta_{E,r}, \beta_{LL,r}, \beta_{KK,r}, \beta_{EE,r}, \beta_{LK,r}, \beta_{LE,r}, \beta_{KE,r}]'$, are further modelled hierarchically as:

$$\boldsymbol{\beta_{p,r}} \sim Normal(\boldsymbol{\beta_{p,j}}, \boldsymbol{\sigma_p^r}) \quad (5.)$$

where $\boldsymbol{\sigma_p^r}$ represents the variability in p-level deviations across regions.

As for the income-specific elasticities for human capital, its lagged effect, and its squared effect $\boldsymbol{\gamma_{q,H\to Y,j}} = \left[\gamma_{H\to Y,j}, \gamma_{H^*\to Y,j}, \gamma_{H^2\to Y,j}\right]$, are modelled hierarchically as:

$$\boldsymbol{\gamma_{q,H\to Y,j}} \sim Normal(\boldsymbol{\gamma_{q,H\to Y}}, \sigma^j_{\gamma_{H\to Y}}) \quad (6.)$$

Where $\boldsymbol{\gamma_{q,H\to Y}} = [\gamma_{H\to Y}, \gamma_{H^*\to Y}, \gamma_{H^2\to Y}]'$ represents the global prior *mean* vector, fixed at zero, and $\sigma^j_{\gamma_{H\to Y}}$ is a scalar representing the standard deviation of income-group-level deviations. The elasticities of human capital, its lagged effect, and its squared term on real GDP per capita are thus modelled as deviations from a zero baseline within a hierarchical framework, forming a $q-$ dimensional vector at the income-group level, where $q = 3$.

Unlike the production elasticities $\boldsymbol{\beta_p}$which are centred on estimated global means, the vectors $\gamma_{H \to Y}$, $\gamma_{H^* \to Y}$ and $\gamma^2_{H \to Y}$ are not assigned its own global prior distribution. This choice reflects both theoretical parsimony and empirical considerations: life expectancy, used as a proxy for human capital, exhibits relatively low variation across countries, reducing the identifiability of a stable global effect. By centring the prior at zero, the model allows income-group and region-level deviations to be informed directly by the data, while avoiding the over-parameterisation that could arise from estimating an additional hyper-mean vector with limited empirical support. This hierarchical structure still enables the model to account for meaningful heterogeneity across income groups and regions, allowing the γ parameters to reflect localised patterns in the relationship between human capital and output while maintaining robustness and interpretability at the global level.

Regional deviations are modelled as:

$$\boldsymbol{\gamma_{q,H \to Y,r}} \sim Normal\left(\boldsymbol{\gamma_{q,H \to Y,j}}, \sigma^r_{\gamma_{H \to Y}}\right) \quad (7.)$$

where $\sigma^r_{\gamma_{H \to Y}}$ is a scalar that captures variability across regions.

At the global level, these elasticities ($\boldsymbol{\beta_p} and\ \boldsymbol{\gamma_{q,H \to Y}}$) serve as baselines for labour, capital, and energy, and their second-order and interaction terms, as well as the current, lagged, and squared contributions of human capital to real GDP per capita. Appropriate priors are assigned to these global-level elasticities, establishing a foundational baseline across all regions and income groups. This approach ensures a centred and flexible framework that allows the data to determine the precise magnitudes of the elasticities while maintaining consistency across hierarchical levels. However, multicollinearity was not tested for interaction variables, presenting an area for further exploration.

In Eq. (4) and (5), the standard deviation $\boldsymbol{\sigma^j_p}$ and $\boldsymbol{\sigma^r_p}$ specifies the variability for each input elasticity (labour, capital, and energy) across income groups, providing flexibility in capturing differences in their economic impacts. In contrast, the contributions of $\boldsymbol{\gamma_{q,H\to Y,j}}$ and $\boldsymbol{\gamma_{q,H\to Y,r}}$ are modelled using a single standard deviation $\sigma^{j}_{\gamma_{H\to Y}}$ and $\sigma^{r}_{\gamma_{H\to Y}}$ respectively. This unified approach reflects the assumption that the effects of current and lagged human capital on GDP share similar underlying drivers across income and region groups, such as commonalities in education systems, healthcare infrastructure, and demographic trends. By using a single standard deviation for both effects, the model captures these shared influences while avoiding over-parameterisation.

Similar to Eqs. (6) and (7), the human capital equation in Eq. (2) employs a hierarchical structure to model the effects of real GDP per capita, its lagged value, and its squared term on human capital.

The income-group-specific elasticities $\boldsymbol{\gamma_{q,Y\to H,j}} = \left[\gamma_{Y^*\to H,j},\ \gamma_{Y\to H,j}, \gamma_{Y^2\to H,j}\right]'$, are modelled hierarchically as:

$$\boldsymbol{\gamma_{q,Y\to H,j}} \sim Normal(\boldsymbol{\gamma_{q,Y\to H}}, \sigma^{j}_{\gamma_{Y\to H}}) \ \ (8.)$$

where $\boldsymbol{\gamma_{q,Y\to H}} = \ [\gamma_{Y\to H},\ \gamma_{Y^*\to H,}, \gamma_{Y^2\to H}]'$, represents the global prior mean vector, fixed at zero, and $\sigma^{j}_{\gamma_{Y\to H}}$ is scalar representing the standard deviation of income-group-level deviations. Regional deviations are further modelled as:

$$\boldsymbol{\gamma_{q,Y\to H,r}} \sim Normal(\boldsymbol{\gamma_{q,Y\to H,j}}, \sigma^{r}_{\gamma_{Y\to H}}) \ \ (9.)$$

where $\sigma^{r}_{\gamma_{Y\to H}}$ is a scalar that captures variability across regions.

This hierarchical formulation from Eq. (6-9) ensures that elasticities are informed by global, income-group, and regional levels. Global elasticities capture broad economic trends, income-group elasticities reflect shared characteristics within advanced or emerging economies, and regional elasticities account for localised variations due to resource availability and institutional settings. This approach provides robust, interpretable estimates by balancing generality and specificity, highlighting structural similarities and differences across OECD economies.

Building on these specifications, the study now extends its focus to estimating and analysing countries' ability to absorb technology from the Global Technological Frontier (GTF). This is quantified using the Direct Absorption Index (DAI), which measures a country's relative position to the evolving Global Technological Frontier (GTF). Although referred to as the GTF, it specifically represents the Global Per Capita Technological Frontier, as the dependent variable in this analysis is real GDP per capita. This distinction emphasises that the frontier is defined in terms of average per capita productivity rather than aggregate economic output. The GTF is modelled as a latent variable, inferred from the observed technological and economic characteristics of all OECD countries through latent variable modelling techniques. This approach recognises that the GTF is not determined by any single country but emerges from the collective innovation efforts of all countries. By capturing the heterogeneous contributions to technological progress, the model also accounts for the dynamic nature of technological leadership over time.

The DAI reflects how effectively a country can adopt advanced technologies from the GTF. A high DAI indicates efficient absorption of technological innovations through channels such as trade, foreign direct investment (FDI), and knowledge spillovers. Countries with strong research ecosystems, a highly skilled labour force, and openness to global markets typically achieve higher DAIs. For OECD countries, the DAI is often linked to economic development, policy effectiveness, and integration into the global economy, highlighting the critical role of institutional frameworks and innovation-driven policies.

The GTF is modelled as a random walk process within a state-space framework. This allows the GTF to evolve flexibly over time, driven by its previous value and stochastic innovations that capture unanticipated shifts in global technology (Triantafyllopoulos, 2021). Unlike fixed or deterministic trends, this approach imposes minimal structure, making it well-suited to represent the non-stationary and uncertain nature of technological progress. It accommodates both smooth transitions and abrupt changes without requiring differencing or ad hoc lag structures (Harvey, 1990).

The latent technological level for each country is modelled as a random walk process, defined as follows:

$$\tau_{i1} \sim Normal(0, \sigma_\tau), \qquad for\ t = 1, \qquad (10)$$
$$\tau_{it} \sim Normal\left(\tau_{i,t-1}, \sigma_\tau\right), \qquad for\ t > 1. \qquad (11)$$

This random walk specification allows for flexible, nonparametric evolution of country-specific technological progress over time, without imposing strong structural assumptions. The latent technological levels for all countries over T time periods are organised into a matrix $\boldsymbol{\tau} \epsilon \mathbb{R}^{I\times T}$, where each row $\boldsymbol{\tau_i} = [\tau_{i1}, \tau_{i2}, \ldots .\tau_{iT}]'$ represents the temporal evolution of technology for country iii. This structure facilitates the representation of country-specific technological trends across time while enabling a coherent global framework for analysing technological progress.

At each time point t, the GTF (τ_t^{GTF}) is defined as the maximum frontier level across all countries:

$$\tau_t^{GTF} = \max_i \tau_{it}. \qquad (12)$$

The GTF across all time periods is then represented as a vector $\boldsymbol{\tau^{GTF}} = [\tau_1^{GTF}, \tau_2^{GTF}, \ldots\ldots, \tau_T^{GTF}]'$. The term τ_t^{GTF} the maximum frontier level at time t, determined by the highest latent technological level across countries. Although this maximum value is the benchmark, it does not imply that a specific country defines the frontier. Instead, it reflects the cumulative technological potential contributed by all countries at that time. This structure ensures that the GTF evolves dynamically, capturing both global technological shifts and country-specific advancements. By framing the GTF as the maximum latent technological level rather than assigning it to a specific country, the model avoids country-specific bias and captures technological progress's inherently global and collective nature. This allows for a realistic representation of global technological dynamics, acknowledging that leadership in technology is shared, competitive, and subject to constant redefinition through international competition and cooperation.

From Eq. (12), the observed technological component of a country (τ_{it}^{O}) can be modelled as:

$$\tau_{it}^{O} \sim Normal\left(\rho_i \cdot \tau_t^{GTF} + (1-\rho_i) \cdot \left(\frac{\tau_t^{GTF}}{u_i}\right), \sigma_\tau^O\right) \qquad (13)$$

For all countries, the observed technological components are represented by the matrix $\boldsymbol{\tau^O}$= $[\tau_{i1}^O, \tau_{i2}^O, \ldots . \tau_{iT}^O]$. The observed technological component includes a normal error term with a standard deviation σ_τ^O to account for discrepancies between observed and latent technological levels. These discrepancies may stem from measurement errors, incomplete data, or unobserved factors. Incorporating this error term in Eq. (13) acknowledges the inherent noise and variability, providing a more realistic representation of the relationship between a country's latent and observed technological states.

In Eq. (13), ρ_i represents the country-specific Direct Absorption Index (DAI), which measures how closely a country aligns with the Global Technological Frontier (GTF). This can be specified as a vector $\boldsymbol{\rho} = [\rho_1, \rho_2, \ldots, \rho_I]'$. The DAI reflects a country's baseline level of technological adoption through direct exposure to the global economy via channels such as international trade, foreign direct investment (FDI), and technology spillovers. It captures the automatic spillover effect resulting from external engagement with the world economy.

Since ρ_i functions as a proportion or efficiency factor, its value is restricted between 0 and 1. A ρ_i value close to 1 indicates that the country can absorb the maximum technological level available through direct spillovers, implying a well-integrated, technologically advanced economy with strong external linkages, open trade policies, and robust innovation networks. Conversely, a ρ_i value closer to 0 indicates minimal direct absorption capacity, reflecting technological isolation, trade restrictions, or limited international engagement. In such cases, a country’s technological progress relies almost entirely on its internal capabilities. $\boldsymbol{\rho}$ is modelled using a truncated Student's t-distribution, constrained between 0 and 1, as it provides heavier tails compared to the Beta distribution. The degrees of freedom (ϑ_ρ) parameter in the t-distribution allows control over the heaviness of the tails, enabling greater flexibility and robustness to outliers while maintaining the bounded nature of $\boldsymbol{\rho}$.

The second term in Eq. (13) introduces u_i, organised as $\boldsymbol{u} = [u_1, u_2, \dots, u_I]$ which represents the Catch-Up Friction Index (CUFI), which represents the internal barriers that slow a country's ability to adopt advanced technologies after direct external absorption. CUFI accounts for domestic factors such as education levels, research and development (R&D) capacity, institutional strength, policy effectiveness, and technological infrastructure. A lower CUFI indicates fewer internal frictions, enabling more efficient and comprehensive technology adoption. Thus, even if a country is exposed to global technology flows, its long-term technological progress depends on how effectively it can overcome internal constraints captured by CUFI.

The CUFI is truncated at 1, meaning its value cannot be less than 1. A CUFI value of 1 indicates no additional internal friction, suggesting that the country can adopt and integrate technology from the GTF at maximum efficiency, assuming full utilisation of available external spillovers. The country faces minimal technological resistance in this ideal scenario, reflecting optimal infrastructure, effective policy frameworks, and a highly skilled workforce.

If CUFI exceeds 1 ($u_i > 1$), internal frictions hinder the country's ability to adopt and utilise new technologies, even when exposed to the GTF. These barriers might include underdeveloped education systems, limited R&D investments, inefficient institutions, or inadequate infrastructure. As u_i increases, the country experiences greater technological resistance, slowing its convergence toward the GTF. To ensure that CUFI remains non-negative, the inefficiency term u_i is modelled using a half-normal distribution, $u_i \sim HalfNormal(1, \sigma_u)$.

This specification ensures that $u_i > 1$, reflecting only restrictive factors that slow technological adoption. The mean of the half-normal distribution is centred at 1, representing a baseline where no additional friction exists. The parameter σ_u controls the spread of the distribution, allowing for variability in internal frictions across countries. Since internal frictions cannot be negative, the truncation at 1 guarantees that CUFI reflects only technological constraints rather than any artificial technological advantage.

The model's dual structure highlights two distinct but interrelated channels of technology adoption. The first channel, direct spillover, governed by the DAI, reflects the technological gains that countries achieve through external engagement with global markets. This term emphasises how much of the GTF a country can adopt automatically due to its international economic integration. The second channel, internal absorption, reflects the country's capacity to transform absorbed technology into tangible progress by leveraging domestic readiness and capacity. CUFI modulates this process by adjusting how efficiently a country can adopt advanced technologies beyond passive absorption.

The model provides a dynamic representation of global technology diffusion by distinguishing between external exposure (DAI) and internal capacity (CUFI). Countries differ in their starting technological levels due to historical, economic, and institutional factors. The separation of external spillovers from internal adoption processes allows the model to account for these disparities while emphasising the potential for technological catch-up through improved domestic capacity.

Bayesian estimation of the model requires specifying the complete data likelihood, integrating both observed and latent variables while accounting for the hierarchical structure of the model. For clarity and brevity, variables are organised into vectors without explicit subscripts, as it is understood that all variables are indexed appropriately by unit i and time t.

The dependent variable in Eq. (1) is denoted as $\boldsymbol{Y} = [\ln Y]$, while the dependent variable for human capital in Eq. (2) is represented as $\boldsymbol{H} = [\ln H]$.

The vector of independent variables, including the constant from Eq. (1), can be represented as:

$$\boldsymbol{X} = [1, lnL, lnK, lnE, (lnL)^2, (lnK)^2, (lnE)^2, (lnL)(lnK), (lnL)(lnE), (lnK)(lnE), lnH, lnH_{t-1}] \qquad (14)$$

Similarly, the vector of independent variables from Eq. (2) can be expressed as:

$$\boldsymbol{Z} = [1, lnY, lnY_{t-1}] \qquad (15)$$

The vector of model parameters, $\boldsymbol{\Omega}$, encompasses all unknown quantities to be estimated. These parameters govern the GDP and human capital equations' hierarchical structure, time-specific effects, and error terms. It can be specified as:

$$\boldsymbol{\Omega} = \begin{bmatrix} \alpha_Y, \boldsymbol{\beta_p}, \boldsymbol{\beta_{p,j}}, \boldsymbol{\beta_{p,r}}, \boldsymbol{\gamma_{q,H\to Y}}, \boldsymbol{\gamma_{q,H\to Y,j}}, \boldsymbol{\gamma_{q,H\to Y,r}}, \alpha_{t,Y}, \boldsymbol{\phi_Y}, \boldsymbol{\tau}, \boldsymbol{\tau^{GTF}}, \boldsymbol{\tau^{O}}, \boldsymbol{\rho}, \vartheta_\rho, \boldsymbol{u}, \vartheta_Y, \boldsymbol{\sigma_p^j}, \boldsymbol{\sigma_p^r}, \sigma^j_{\gamma_{H\to Y}}, \sigma^r_{\gamma_{H\to Y}}, \sigma_{\alpha_{t,Y}}, \sigma_{v_Y}, \sigma_\tau, \sigma_\tau^O, \sigma_u \\ \theta, \alpha_H, \boldsymbol{\gamma_{q,Y\to H}}, \boldsymbol{\gamma_{q,Y\to H,j}}, \boldsymbol{\gamma_{q,Y\to H,r}}, , \alpha_{t,Y}, \boldsymbol{\phi_Y}, \vartheta_H, \sigma^j_{\gamma_{Y\to H}}, \sigma^r_{\gamma_{Y\to H}} \end{bmatrix} \quad (16)$$

The complete data likelihood integrates the hierarchical priors and observed variables across both equations:

$$\begin{aligned} P(\boldsymbol{Y}, \boldsymbol{H}|\boldsymbol{\Omega}) = {} & P\left(\boldsymbol{Y}|\boldsymbol{X}, \alpha_Y, \boldsymbol{\beta_{p,r}}, \boldsymbol{\gamma_{q,H\to Y,r}}, \alpha_{t,Y}, \boldsymbol{\phi_Y}, \boldsymbol{\tau}, \vartheta_Y, \sigma_{v_Y}\right) \times P\left(\boldsymbol{H}|\boldsymbol{Z}, \alpha_H, \boldsymbol{\gamma_{q,Y\to H,r}}, \alpha_{t,H}, \boldsymbol{\phi_H}, \vartheta_H, \sigma_{v_H}\right) \\ & \times P\left(\boldsymbol{\beta_{p,r}}|\boldsymbol{\beta_{p,j}}, \boldsymbol{\sigma_p^r}\right) \times P\left(\boldsymbol{\beta_{p,j}}|\boldsymbol{\beta_p}, \boldsymbol{\sigma_p^j}\right) \times P\left(\boldsymbol{\gamma_{q,H\to Y,r}}|\boldsymbol{\gamma_{q,H\to Y,j}}, \sigma^r_{\gamma_{H\to Y}}\right) \times P\left(\boldsymbol{\gamma_{q,H\to Y,j}}|\gamma_{H\to Y}, \sigma^j_{\gamma_{H\to Y}}\right) \\ & \times P\left(\boldsymbol{\gamma_{q,Y\to H,r}}|\boldsymbol{\gamma_{q,Y\to H,j}}, \sigma^r_{\gamma_{Y\to H}}\right) \times P\left(\boldsymbol{\gamma_{q,Y\to H,j}}|\gamma_{Y\to H}, \sigma^j_{\gamma_{Y\to H}}\right) \times P\left(\alpha_{t,Y}, \alpha_{t,H}|\theta, \sigma_{\alpha_{t,Y}}, \sigma_{\alpha_{t,H}}\right) \times P(\boldsymbol{\tau}|\sigma_\tau) \\ & \times P(\boldsymbol{\tau^O}|\boldsymbol{\tau^{GTF}}, \sigma_\tau^O, \boldsymbol{\rho}, \boldsymbol{u}) \times P\left(\boldsymbol{\rho}|\vartheta_\rho\right) \times P(\boldsymbol{u}|\sigma_u) \qquad (17) \end{aligned}$$

The likelihood is directly connected to the hierarchical specifications of the model. From Eq. (4) and (5), the region-specific elasticities $\left(\boldsymbol{\beta_{p,r}}\right)$ are modelled as deviations from income-group-specific elasticities $\left(\boldsymbol{\beta_{p,j}}\right)$ and global elasticities $\left(\boldsymbol{\beta_p}\right)$, capturing both localised regional variations and broader income-group-level trends. From Eq. (6) and (7), the human capital elasticities $\left(\boldsymbol{\gamma_{H\to Y,r}}\right)$ and their lagged effects are modelled hierarchically as deviations from income-group-specific elasticities $\left(\boldsymbol{\gamma_{H\to Y,j}}\right)$, which themselves deviate from global elasticities $(\gamma_{H\to Y})$. From Eq. (8) and (9), the GDP effects on human capital $(\boldsymbol{\gamma_{Y\to H,r}})$ and $(\boldsymbol{\gamma_{Y\to H,j}})$ follow a similar hierarchical structure, with regional deviations modelled as deviations from income-group-specific effects and income-group-specific deviations modelled relative to global effects.

Residuals $(v_{Y,it})$ and $(v_{H,it})$ are modelled using Student's t distributions, with degrees of freedom (ϑ_Y) and (ϑ_H) and standard deviation (σ_{v_Y}) and (σ_{v_H}). For time-specific effects, the terms for GDP $(\alpha_{t,Y})$ and human capital $(\alpha_{t,H})$ are jointly modelled through a bivariate normal distribution, as specified in Eq. (3). The latent technological levels $(\boldsymbol{\tau})$ are modelled dynamically using the hierarchical structure specified in Eq. (10) and (11). The observed technological components ($\boldsymbol{\tau^{O}}$) are linked to the latent levels through the structure in Eq. (13) and capture the relationship between a country's proximity to the Global Technological Frontier ($\boldsymbol{\tau^{GTF}}$), the Direct Absorption Index ($\boldsymbol{\rho}$), and the Catch-Up Friction Index ($\boldsymbol{u}$).

Therefore, the complete data likelihood in parametric form based on Eq. (17) can be expressed as:

$$
\begin{aligned}
&\mathcal{L}(\boldsymbol{\Omega}|\boldsymbol{Y},\boldsymbol{H})\\
&=\prod_{i=1}^{I}\prod_{t=1}^{T}\left[\frac{\Gamma\left(\frac{\vartheta_Y+1}{2}\right)}{\sqrt{\vartheta_Y\pi}\,\sigma_{v_Y}\Gamma\left(\frac{\vartheta_Y}{2}\right)}\left(1+\frac{\left(Y_{it}-\mu_{Y,it}\right)^2}{\vartheta_Y\sigma_{v_Y}^2}\right)^{-\frac{\vartheta_Y+1}{2}}\cdot\frac{\Gamma\left(\frac{\vartheta_H+1}{2}\right)}{\sqrt{\vartheta_H\pi}\,\sigma_{v_H}\Gamma\left(\frac{\vartheta_H}{2}\right)}\left(1+\frac{\left(H-\mu_{H,it}\right)^2}{\vartheta_H\sigma_{v_H}^2}\right)^{-\frac{\vartheta_H+1}{2}}\right]\\
&\times\prod_{q=1}^{Q}\left[\prod_{r=1}^{R}\frac{1}{\sqrt{2\pi}\sigma_{\gamma_{H\to Y}}^{r}}exp\left(-\frac{\left(\gamma_{q,H\to Y,r}-\gamma_{q,H\to Y,j}\right)^2}{2\left(\sigma_{\gamma_{H\to Y}}^{r}\right)^2}\right)\cdot\prod_{j=1}^{J}\frac{1}{\sqrt{2\pi}\sigma_{\gamma_{H\to Y}}^{j}}exp\left(-\frac{\left(\gamma_{q,H\to Y,j}-\gamma_{H\to Y}\right)^2}{2\left(\sigma_{\gamma_{H\to Y}}^{j}\right)^2}\right)\right]\\
&\times\prod_{q=1}^{Q}\left[\prod_{r=1}^{R}\frac{1}{\sqrt{2\pi}\sigma_{\gamma_{Y\to H}}^{r}}exp\left(-\frac{\left(\gamma_{q,Y\to H,r}-\gamma_{q,Y\to H,j}\right)^2}{2\left(\sigma_{\gamma_{Y\to H}}^{r}\right)^2}\right)\cdot\prod_{j=1}^{J}\frac{1}{\sqrt{2\pi}\sigma_{\gamma_{Y\to H}}^{j}}exp\left(-\frac{\left(\gamma_{q,Y\to H,j}-\gamma_{Y\to H}\right)^2}{2\left(\sigma_{\gamma_{Y\to H}}^{j}\right)^2}\right)\right]\\
&\times\prod_{t=1}^{T}\frac{1}{2\pi\sigma_{\alpha_{t,Y}}\sigma_{\alpha_{t,H}}\sqrt{1-\theta^2}}exp\left(-\frac{1}{2(1-\theta^2)}\left[\frac{\alpha_{t,Y}^2}{\sigma_{\alpha_{t,Y}}^2}+\frac{\alpha_{t,H}^2}{\sigma_{\alpha_{t,H}}^2}-\frac{2\theta\alpha_{t,Y}\alpha_{t,H}}{\sigma_{\alpha_{t,Y}}\sigma_{\alpha_{t,H}}}\right]\right)\\
&\times\prod_{i=1}^{I}\prod_{t=1}^{T}\begin{cases}\frac{1}{\sqrt{2\pi}\sigma_\tau}exp\left(-\frac{\tau_{i1}^2}{2\sigma_\tau^2}\right), & if\ t=1\\ \frac{1}{\sqrt{2\pi}\sigma_\tau}exp\left(-\frac{(\tau_{it}-\tau_{it-1})^2}{2\sigma_\tau^2}\right), & if\ t>1\end{cases}\\
&\times\prod_{i=1}^{I}\prod_{t=1}^{T}\frac{1}{\sqrt{2\pi}\sigma_\tau^{O}}exp\left(-\frac{\left(\tau_{it}^{o}-\left[\rho_i\tau^{GTF}+(1-\rho_i)\frac{\tau^{GTF}}{u_i}\right]\right)^2}{2(\sigma_\tau^{O})^2}\right)\\
&\times\prod_{i=1}^{I}\frac{\Gamma\left(\frac{\vartheta_\rho+1}{2}\right)}{\sqrt{\vartheta_\rho\pi}\,\sigma_\rho\Gamma\left(\frac{\vartheta_\rho}{2}\right)}\left(1+\frac{\left(\rho_i-\mu_\rho\right)^2}{\vartheta_\rho\sigma_\rho^2}\right)^{-\frac{\vartheta_\rho+1}{2}}\\
&\times\prod_{i=1}^{I}\frac{1}{\sqrt{2\pi}\sigma_u}exp\left(\frac{u_i^2}{2\sigma_u^2}\right) \qquad (18)
\end{aligned}
$$

In Eq. (18) the terms in the parametric form of the complete data likelihood, the terms $\mu_{Y,it}$ and $\mu_{H,it}$ represent the expected values of GDP and human capital, defined in Eq. (1) and (2) respectively. Additionally, the symbol Γ refers to the gamma function, which is integral to the Student's t distribution. It ensures proper normalisation of the distribution and facilitates the modelling of heavy-tailed data, making the model robust against outliers and extreme observations.

In the Bayesian framework, priors are essential for incorporating prior knowledge and regularising parameters in hierarchical models. Both the dependent and independent variables in the model were standardised such that the first-order terms can be interpreted as elasticities at the geometric mean. Standardising the dependent variable to the geometric mean ensures that the model parameters, particularly the coefficients, are more interpretable and reflect proportional changes relative to the central tendency of the data. Standardising variables also improves model stability and ensures that the priors for both the mean and scale can remain small and appropriately regularising.

For the GDP model, the intercept α_Y is assigned a normal prior with mean 0 and standard deviation 2, while the global term coefficients vector $\boldsymbol{\beta_p}$ is given normal priors with mean 0 and standard deviation 1.2. On the other hand, for human capital intercepts α_H is given slightly tighter normal priors with a mean of 0 and a standard deviation of 0.5. This reflects the expectation that variations in life expectancy are generally smaller and more stable compared to the broader economic fluctuations captured in GDP. Life expectancy changes are often more gradual and less volatile than GDP, warranting a tighter prior to regularising the model and preventing overestimation of intercept effects, thereby improving stability and interpretability.

For the GDP model, the global term coefficients vector $\boldsymbol{\beta_p}$ is given normal priors with a mean of 0 and a standard deviation of 1.2. Income-specific deviations ($\boldsymbol{\beta_{p,j}}$) and region-specific deviations ($\boldsymbol{\beta_{p,r}}$) for these coefficients are modelled as normal distributions centred on the group-level means, with standard deviations $\boldsymbol{\sigma_p^j}$ and $\boldsymbol{\sigma_p^r}$, respectively. These standard deviations are assigned half-normal priors truncated below zero, with $\boldsymbol{\sigma_p^j} \sim Half - Normal(0,0.25)$ and $\boldsymbol{\sigma_p^r} \sim Half - Normal(0,0.50)$. The smaller scale for income-based deviations reflects the expectation that variations in GDP across income groups are less pronounced than across regions, as income groups are broader and inherently more homogeneous than regions, which can exhibit significant structural and contextual differences.

The half-normal prior constrains the standard deviations to positive values while allowing for small yet flexible variations. This approach regularises the estimates, ensuring that the standard deviations remain reasonable and reduces the risk of overfitting. In hierarchical models, this regularisation is particularly important, as excessive flexibility in parameter estimates can lead to instability. In contrast, the half-normal prior provides a principled way to balance flexibility and control.

For the effect of human capital on GDP, given that the variables were standardised, the effect of human capital on GDP, its lag, and their square terms through $\boldsymbol{\gamma_{q,H\to Y,j}}$ is given a mean of zero and small standard deviations, specifically $\sigma^{r}_{\gamma_{H\to Y}} \sim Half - Normal(0,0.05)$ and $\sigma^{j}_{\gamma_{H\to Y}} \sim Half - Normal(0,0.05)$. Similarly, the parameters corresponding to the effect of GDP on human capital through $\boldsymbol{\gamma_{q,H\to Y,r}}$ and their standard deviations $\sigma^{r}_{\gamma_{Y\to H}}$ and $\sigma^{j}_{\gamma_{Y\to H}}$ are given the same priors.

Standardisation ensures that the variables are measured on a comparable scale, where deviations represent standardised units. As a result, the first-order coefficients, their lag, and their square terms reflect proportional changes in standardised terms. A mean of zero aligns with the prior belief that, in the absence of strong evidence to the contrary, these effects are not inherently biased toward positive or negative values.

The use of small standard deviations, modelled as half-normal distributions, regularises the model by constraining the potential size of these coefficients. This is particularly important because square terms and lagged effects can introduce additional flexibility, which, if unbounded, could lead to overfitting or spurious relationships. The small scale of 0.05 reflects the expectation that the standardised human capital variables contribute incrementally to GDP variations, ensuring that the model remains interpretable and stable.

Country-specific autoregressive coefficients ($\boldsymbol{\phi_Y}$) and ($\boldsymbol{\phi_H}$) follow truncated normal priors with mean 0, standard deviation 0.5, and bounds between -1 and 1, ensuring invertibility and stabilising the moving average process.

For the technological frontier, the time-varying latent technological frontier ($\boldsymbol{\tau}$) is modelled with normal priors for each time period, with standard deviations $\sigma_\tau \sim Half - Normal(0{,}0.05)$, reflects the expectation that changes in the technological frontier are gradual and constrained over time, ensuring stability and regularisation in the model. Similarly, the scale of observed technological component σ_τ^O is also given $Half - Normal(0{,}0.05)$.

The absorption rate ($\boldsymbol{\rho}$) is modelled using a truncated Student's *t*-distribution with parameters reflecting income groups. For advanced countries, $\boldsymbol{\rho}$ follows a $student - t\ (\vartheta_\rho, 0.90{,}0.20)$ distribution truncated to [0,1], indicating they are closer to the global technological frontier. For emerging countries, $student - t\ (\vartheta_\rho, 0.70{,}0.25)$ distribution truncated to [0,1] reflects their position farther from the frontier. The wider standard deviation (0.25) for emerging countries reflects their greater variability in technological absorption rates due to diverse economic, institutional, and infrastructural factors.

The degrees of freedom parameter (ϑ_ρ) is assigned a $Gamma\ (2, 0.50)$ prior, which allows flexibility in the heaviness of the tails to robustly handle outliers while still encouraging reasonable concentration around the mean.

Resistance to technological change ($\boldsymbol{u}$) is assigned a log-normal prior (mean≈1.0) with a smaller variance (0.15) for advanced countries to reflect lower resistance and a larger variance (0.3) for emerging countries to capture their greater variability in resistance while still permitting posterior updates based on the data.

The correlation θ between time effects for GDP ($\alpha_{t,Y}$) and human capital ($\alpha_{t,H}$) is represented by a correlation matrix assigned a Lewandowski-Kurowicka-Joe (LKJ) prior with a shape parameter of 1. The LKJ(1) prior is uniform over all valid correlation matrices, introducing no bias toward specific correlation structures and allowing the data to determine the posterior correlations (Lewandowski et al., 2009). The $Half - Normal(0,0.15)$ on $\sigma_{\alpha_{t,Y}}$ and $\sigma_{\alpha_{t,H}}$ regularises the standard deviations, reflecting the belief that global shocks induce small but meaningful time-specific effects.

Finally, the residual standard deviations (σ_{v_Y}) and (σ_{v_H}) are modelled using half-normal priors with small standard deviations (0.05). This reflects the expectation of low residual noise, as the dependent variables have been standardised by their geometric mean, which adjusts the units of measurement without altering the underlying variability. The degrees of freedom for the Student's t distributions (ϑ_Y) and (ϑ_H) follow Gamma (2,0.5) priors, allowing for flexibility in capturing heavy-tailed residuals while ensuring robust posterior inference.

The 'No-U-Turn Sampler' (NUTS[2]), a state-of-the-art extension of the Hamiltonian Monte Carlo (HMC) algorithm was used to draw samples from the posterior distribution. The model was estimated using CmdStanR[3], running five parallel Markov chains, each with 4,000 iterations (2,000 warm-up and 2,000 sampling), yielding 10,000 post-warmup samples in total.

To ensure accurate and stable sampling in the presence of complex posterior geometry, the sampler was configured with a max_treedepth of 14, allowing longer Hamiltonian trajectories when needed. An adapt_delta of 0.999 was used to increase the target acceptance probability, reducing the risk of divergent transitions and improving exploration of high-curvature regions of the posterior. These settings were selected to prioritise numerical stability and robustness of inference.

All key diagnostic measures confirmed reliable sampling: no divergent transitions were observed, and all Gelman–Rubin statistics ($\hat{R}$) were below 1.01, indicating proper mixing across chains (Gelman et al., 2013; Gelman & Rubin, 1992). The full model code and dataset are provided in the supplementary materials to facilitate transparency and replication. Trace plots for a subset of key

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[2] For detailed explanation of NUTS algorithm refer to Hoffman and Gelman (2014).

[3] CmdStanR is the R interface to CmdStan, developed by the Stan Development Team. See: https://mc-stan.org/cmdstanr

parameters are displayed in Appendix A1 to illustrate sampling behaviour across chains. Trace plots for all model parameters can be generated using the accompanying replication code.

Chapter 5 – Empirical Results

To estimate elasticities within a translog production framework, three models were developed and evaluated. The Income Level Coefficients Model allows elasticities to vary based on whether a country is classified as emerging or advanced, capturing structural differences in production efficiency across income groups. The Region Level Coefficients Model introduces geographic heterogeneity by allowing elasticities to differ across regions, reflecting spatial variation in economic behaviour. Finally, the Hierarchical Level Coefficients Model integrates both approaches by modelling region-level coefficients informed by income classifications. This hierarchical structure enables a flexible yet consistent representation of production elasticities, balancing global income-based classifications with region-specific economic patterns.

A hybrid validation approach was employed to assess model performance and generalisability, combining 10-fold cross-validation with a temporal cutoff at time period 15. In the 10-fold validation, countries were divided into ten mutually exclusive groups (folds). In each iteration, one-fold – comprising a subset of countries – was entirely excluded from the training dataset and used solely for testing. This ensured that model evaluation was based on genuinely unseen national economies, preventing data leakage and providing a robust assessment of spatial generalisation.

Temporal validation further tested the models' predictive capabilities by restricting training data to time periods 1–15, while predictions were evaluated on time periods 16–22. This setup closely mimicked real-world forecasting challenges, assessing how well the models could extrapolate beyond observed economic trends. To provide an integrated assessment, combined metrics were computed by evaluating both holdout entities and temporal extrapolation together, offering a holistic measure of each model's ability to generalise across space and time.

Key metrics used for evaluation included RMSE (Root Mean Square Error), MSE (Mean Square Error), and MAE (Mean Absolute Error), which collectively capture both absolute and relative prediction errors. To further assess model fit while accounting for complexity, Bayesian model selection was performed using a combined WAIC (Watanabe-Akaike Information Criterion) and LOO-CV (leave-one-out cross-validation) approach, incorporating all data points from both spatial holdout and temporal extrapolation tests. This integrated evaluation ensured that model selection was not driven solely by in-sample fit but rather reflected broader generalisation across both dimensions. WAIC provides a measure of predictive accuracy while penalising model complexity to prevent overfitting, whereas LOO-CV systematically omits individual observations to estimate out-of-sample predictive performance, offering a robust validation of model reliability.

For GDP predictions, the Hierarchical Level Coefficients model demonstrated the best performance for holdout entities, achieving the lowest RMSE (0.9242), MSE (0.8876), and MAE (0.7573). The Region Level Coefficients model followed closely, with RMSE of 0.9247, MSE of 0.8889, and MAE of 0.7575. The Income Level Coefficients model showed slightly weaker results, with RMSE of 0.9251, MSE of 0.8896, and MAE of 0.7582. In temporal extrapolation, the Region Level Coefficients model performed marginally better than the others, achieving RMSE of 0.9874, MSE of 0.9828, and MAE of 0.7799. The Hierarchical Level Coefficients model closely followed, with RMSE of 0.9880, MSE of 0.9841, and MAE of 0.7803. The Income Level Coefficients model showed similar, but slightly less accurate performance, with RMSE of 0.9878, MSE of 0.9835, and MAE of 0.7808.

For Human Capital predictions, the Income Level Coefficients model performed best for holdout entities, achieving the lowest RMSE (0.0493) and MSE (0.0025). The Hierarchical and Region Level Coefficients models followed closely, both achieving RMSE of approximately 0.0499 and MSE of 0.0026. In temporal extrapolation, the Income Level Coefficients model maintained its edge with RMSE of 0.0551 and MSE of 0.0031, though its MAE (0.0445) was slightly higher than the Region and Hierarchical models, which both achieved MAE of 0.0441.

The combined approach, which evaluates both holdout and temporal validation together, underscores the robustness of the Hierarchical Level Coefficients model in capturing spatial and temporal generalisation. In this context, metrics like WAIC (Watanabe-Akaike Information Criterion) and LOO (Leave-One-Out Cross-Validation) are particularly significant. WAIC evaluates how well the model balances predictive accuracy and complexity by penalising overfitting, while LOO provides a robust measure of predictive accuracy by systematically leaving out individual data points during validation. These metrics integrate performance across both spatial and temporal dimensions, offering a holistic assessment of model reliability.

For combined metrics in GDP predictions, the Region Level Coefficients model achieved slightly better RMSE (0.9739) and MSE (0.9557). However, the Hierarchical Level Coefficients model exhibited superior fit with a WAIC of -2298.80 and LOO of -2287.77, compared to the Region Level model's WAIC of -2221.37 and LOO of -2215.88. These results highlight the Hierarchical model's ability to balance predictive accuracy and complexity effectively, ensuring robust generalisation across diverse spatial and temporal contexts.

For combined metrics in Human Capital predictions, the Region Level Coefficients model achieved the best MAE (0.0432), while the Hierarchical Level Coefficients model provided nearly identical RMSE (0.0543) and MSE (0.0030). In terms of model fit, the Hierarchical model demonstrated strong generalisation with a WAIC of -3005.96 and LOO of -3004.82, which were closely comparable to the Region Level model's WAIC of -3006.10 and LOO of -3005.17. These scores indicate that while the Region Level model slightly outperformed in specific accuracy metrics, the Hierarchical model maintained a better balance between complexity and predictive reliability.

Overall, the Hierarchical Level Coefficients Model's superior performance in WAIC and LOO for the combined approach highlights its robustness and reliability. By capturing the bidirectional feedback between GDP and human capital while balancing predictive accuracy with model complexity, this model provides the most comprehensive and consistent framework for analysing spatial and temporal economic dynamics. Its ability to integrate both income-based and regional parameterisations allows it to account for local variations while maintaining coherence with broader global trends, ensuring a flexible yet structured approach to production elasticity estimation.

Given these advantages, the analysis centres on the hierarchical model specification, which flexibly captures group-level heterogeneity across regions and development levels. Full posterior estimates for all model variants, including hierarchical, income-based (Advanced/Emerging countries) and region-specific, are reported in Appendices A2 through A4.

To facilitate interpretation, all continuous variables were log-transformed and standardised, allowing first-order coefficients to be interpreted as elasticities at the geometric mean. This means that each estimated coefficient reflects the percentage change in real GDP per capita associated with a 1% change in the corresponding predictor, evaluated at the central tendency of the data. Quadratic and interaction terms offer insight into nonlinearities and complementarity between inputs.

Table 2 reports posterior means from the hierarchical model, with regions nested within broader development categories (Advanced and Emerging Economies). The estimates reflect regional variation while borrowing strength from the development group structure. The results highlight several consistent patterns, as well as notable regional variations, in the elasticity of output and human capital with respect to labour, capital, energy use, and human capital accumulation.

Based on the estimated parameters in Table 2, on average, a 1% increase in average employed labour per capita is associated with a 0.417% increase in average real GDP per capita in Oceania, 0.465% in Europe, 0.354% in the Americas, and 0.494% in Asia. The effect is slightly stronger in advanced economies (0.423%) than in emerging economies (0.397%), suggesting that labour productivity plays a significant role in GDP per capita growth in wealthier nations. However, in emerging economies, the credible interval includes zero, indicating uncertainty in the average effect of labour on GDP per capita.

Table 2

Posterior Means for the Hierarchical Specification

Parameter	Oceania	Europe	Americas	Asia	Advanced	Emerging
GDP Equation						
$\beta_{log\ (labour)}$	0.417*	0.465*	0.354*	0.494*	0.423*	0.397
$\beta_{log(capital)}$	0.13*	0.23*	0.19*	0.259*	0.204*	0.186
$\beta_{log(energy)}$	0.131	0.144*	0.148*	0.163*	0.144*	0.157
$\gamma_{log\ (human\ capital)}$	0.056	0.061	0.063	0.152	0.063	-0.002
$\beta_{log\ (labour)^2}$	0.775	1.08*	0.526	0.882*	0.765	0.745
$\beta_{log\ (capital)^2}$	-0.015	-0.033*	0.037*	0.053*	0.014	0.055
$\beta_{log\ (energy)^2}$	-0.706*	0.099*	-0.106*	0.327	-0.09	-0.098
$\gamma_{log\ (human\ capital)^2}$	-0.006	-0.018	-0.007	-0.007	-0.008	-0.001
$\beta_{log\ (labour) \times log(capital)}$	-0.258	0.059*	0.193*	-0.153*	-0.048	-0.023
$\beta_{log\ (labour) \times log(energy)}$	-0.174	-0.555*	0.28*	0.075	-0.065	-0.033
$\beta_{log\ (capital) \times log(energy)}$	-0.031	-0.014	-0.066*	-0.120*	-0.064	-0.053
$\gamma_{log\ (human\ capital), t-1}$	-0.004	-0.022	0.000	0.035	0.001	0.001
Human Capital Equation[4]						
$\gamma_{log\ (real\ gdp\ per\ capita)}$	0.032*	0.036*	-0.001	0.089*	0.024	-0.001
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.014	-0.029*	-0.026*	0.023*	-0.007	0.00
$\gamma_{log\ (real\ gdp\ per\ capita), t-1}$	0.012	0.012*	-0.001	-0.005	0.004	0.00

*where the 90 % credible interval does not include zero

This uncertainty is likely due to the hierarchical structure of the model, where regional estimates borrow strength from income-group estimates. While this improves precision at the regional level, estimates at the income-group level retain greater variability before being further refined by regional effects. Additionally, the smaller sample size of emerging economies (12 countries vs. 25 advanced

[4] When the residual plots of the human capital equation were inspected for each country, significant autocorrelation is observed in a few cases (approximately 3–4 countries). To mitigate this, an alternative specification is estimated that included a lag of the dependent variable in the human capital equation, with country-specific coefficients. This effectively addressed the residual autocorrelation in those countries. However, the inclusion of the lagged dependent variable did not materially alter the estimated coefficients of the other covariates. Given that this specification complicates the interpretation of short- versus long-run effects, these results are not presented in the main paper. Nonetheless, they are available from the authors upon request.

economies) results in wider credible intervals, as fewer observations make it harder to precisely estimate the average effect of labour on GDP per capita.

For capital elasticities, a 1% increase in average gross fixed capital per capita is associated with a 0.13% rise in average real GDP per capita in Oceania, 0.23% in Europe, 0.19% in the Americas, and 0.259% in Asia. The effect is comparable between advanced (0.204%) and emerging economies (0.186%), though the credible interval for emerging economies includes zero, indicating greater uncertainty at the income-group level. The higher elasticity in Asia and Europe suggests these regions benefit more from capital investment, likely due to better infrastructure, industrial expansion, or technological adoption. For instance, increased spending on infrastructure and the adoption of (energy-saving) technologies in Central Europe have facilitated a growth in GFCF by 7.1 per cent year-over-year in the second quarter of 2023 (Izvorski et al.). Developments in investment patterns in Europe highlight the significance of high-quality infrastructure and technological adoption to maximise benefits from capital investment.

For energy consumption per capita, a 1% increase is associated with a 0.144% increase in real GDP per capita in Europe, 0.148% in the Americas, and 0.163% in Asia. The effect is uncertain in Oceania (0.131%) and emerging economies (0.157%), where the credible interval includes zero. This suggests that energy consumption is more directly linked to economic growth in Europe, the Americas, and Asia, potentially due to energy-intensive industries. The uncertainty in emerging economies could stem from variations in energy access, infrastructure, or data limitations at the income-group level.

The effect of human capital per capita (proxied by life expectancy) on GDP per capita varies across regions. The estimated elasticity is 0.056 in Oceania, 0.061 in Europe, 0.063 in the Americas, 0.152 in Asia, 0.063 in advanced economies, and -0.002 in emerging economies. The credible intervals for these estimates include zero, indicating that the effect is not statistically distinguishable from zero in these regions. This statistically insignificant result may occur due to relatively static life expectancies in the OECD over the observed period. For instance, countries such as the United States had a life expectancy from birth of 76.64 in 2000, compared to 76.33 in 2021 (The World Bank, 2023b).

The squared terms provide insight into diminishing or increasing returns to labour, capital, and energy across regions. In Europe (1.08), labour exhibits increasing returns, possibly due to labour specialisation or institutional efficiencies. In contrast, the effect in the Americas (0.526) is uncertain, as the credible interval includes zero. This suggests that while the estimated elasticity is positive, there is not enough statistical certainty to conclude that additional labour per capita significantly contributes to GDP growth in the region.

Capital exhibits diminishing returns in Europe (-0.033) but increasing returns in the Americas (0.037) and Asia (0.053), suggesting that capital accumulation remains a strong growth driver in these regions. For energy consumption, diminishing returns are observed in Oceania (-0.706) and the Americas (-0.106), meaning that additional energy use contributes less to GDP growth. However, in Europe (0.099), the effect remains positive, indicating that energy consumption continues to play a role in economic expansion. For other regions, the credible intervals include zero, indicating uncertainty in whether labour, capital, or energy exhibits strong increasing or diminishing returns.

The interaction between labour and capital is positive in Europe (0.059) and the Americas (0.193), suggesting that capital investment enhances labour productivity in these regions. In contrast, Asia (-0.153) shows a negative interaction, indicating that labour and capital act as substitutes, possibly due to automation or capital-intensive industries reducing reliance on labour.

For labour and energy, the interaction is strongly negative in Europe (-0.555), implying that improvements in energy efficiency reduce the need for labour. However, in the Americas (0.28), the interaction is positive, suggesting that industries still rely on both labour and energy inputs for production.

For capital and energy, the interaction is negative in the Americas (-0.066), and Asia (-0.120), indicating that as capital stock increases, the marginal contribution of energy declines. This could reflect greater energy efficiency in capital-intensive industries, where modern technology reduces energy dependence.

The relationship between real GDP per capita and human capital (proxied by life expectancy) varies across regions. In Asia and Europe, a 1% increase in average real GDP per capita is associated with a 0.089% and 0.036% increase in average life expectancy, respectively. This suggests that economic growth in these regions is linked to improvements in healthcare access, living conditions, and overall well-being.

In contrast, the effect in the Americas of the estimated elasticity of life expectancy with respect to GDP per capita is -0.001, but the credible interval includes zero. This means there is no strong statistical evidence to confirm whether higher real GDP per capita systematically influences life expectancy in the region. The uncertainty suggests that factors such as public health investment, income distribution, or social policies may play a role. However, the data does not provide clear support for a positive or negative relationship.

The squared GDP term is negative in Europe (-0.029) and the Americas (-0.026), suggesting diminishing returns; at higher income levels, additional economic growth contributes less to further improvements in life expectancy. In Asia (0.023), however, the effect remains positive, indicating that economic expansion continues to support human capital accumulation.

In Europe, a 1% increase in lagged real GDP per capita is associated with a 0.012% increase in life expectancy, with a credible interval that does not include zero, suggesting that past economic growth has a delayed impact on life expectancy. In all other regions, the credible intervals include zero, and no other lagged effects were certain. In addition to estimating production elasticities, a key contribution of this study lies in quantifying the extent to which economies effectively absorb technological progress and the degree to which they experience friction in catching up with the global technological frontier. Building upon the hierarchical multilevel framework, the empirical results now focus on the Direct Absorption Index (DAI, $\boldsymbol{\rho}$) and the Catch-Up Friction Index (CUFI, $\boldsymbol{u}$), as specified in Equation (13). These two indices capture technological diffusion's external and internal dimensions across OECD economies.

The DAI (ρ_i) measures how closely a country aligns with the Global Technological Frontier (GTF). A higher ρ_i (closer to 1) suggests that the country efficiently integrates external technological spillovers via international trade, FDI, and cross-border knowledge flows. Conversely, a lower ρ_i indicates that the economy is relatively isolated from global technological diffusion due to restrictive trade policies, limited foreign investment, or structural barriers. Meanwhile, the CUFI (u_i) represents domestic constraints on technology adoption. Even if a country is externally exposed to the GTF, internal frictions, such as weak institutions, insufficient R&D investment, or low education levels, can slow down technological integration. A CUFI value of 1 suggests that the country efficiently absorbs all available technology, while u_i > 1 indicates increasing barriers to adoption.

These two components interact to shape a country's long-run technological trajectory. Table 3 presents the ranked estimates for both indices, classifying countries into high, medium, and low categories based on their absorption capabilities and resistance levels to provide a clear comparative perspective.

Table 3
Empirical Estimates of Technological Absorption and Friction

Rank	Country	DAI	CUFI	Technological Component	Absorption	Resistance
1	Switzerland	0.91	1.04	5.52	High Absorption	Low Resistance
2	United States	0.87	1.07	5.50	High Absorption	Low Resistance
3	United Kingdom	0.86	1.06	5.50	High Absorption	Low Resistance
4	Australia	0.77	1.14	5.41	High Absorption	Low Resistance
5	Germany	0.77	1.12	5.42	High Absorption	Low Resistance
6	France	0.68	1.17	5.32	Medium Absorption	Medium Resistance
7	Norway	0.65	1.18	5.32	Medium Absorption	Medium Resistance

8	Luxembourg	0.65	1.18	5.28	Medium Absorption	Medium Resistance
9	Italy	0.57	1.20	5.21	Medium Absorption	Medium Resistance
10	Ireland	0.54	1.22	5.13	Medium Absorption	Medium Resistance
11	Japan	0.53	1.22	5.13	Medium Absorption	Medium Resistance
12	Netherlands	0.50	1.23	5.09	Low Absorption	Medium Resistance
13	Sweden	0.49	1.22	5.09	Low Absorption	Medium Resistance
14	Canada	0.49	1.24	5.06	Low Absorption	Medium Resistance
15	Denmark	0.48	1.23	5.08	Low Absorption	Medium Resistance
16	Austria	0.44	1.25	4.97	Low Absorption	Medium Resistance
17	Spain	0.41	1.26	4.92	Low Absorption	Medium Resistance
18	Belgium	0.40	1.26	4.90	Low Absorption	Medium Resistance
19	Finland	0.37	1.28	4.82	Low Absorption	Medium Resistance
20	New Zealand	0.35	1.28	4.81	Low Absorption	Medium Resistance
21	Israel	0.32	1.28	4.77	Low Absorption	Medium Resistance
22	Korea	0.28	1.32	4.61	Low Absorption	High Resistance
23	Iceland	0.23	1.35	4.47	Low Absorption	High Resistance
24	Turkiye	0.21	1.36	4.41	Low Absorption	High Resistance
25	Greece	0.19	1.38	4.33	Low Absorption	High Resistance
26	Portugal	0.16	1.40	4.23	Low Absorption	High Resistance
27	Mexico	0.15	1.42	4.17	Low Absorption	High Resistance
28	Poland	0.13	1.43	4.11	Low Absorption	High Resistance
29	Chile	0.12	1.45	4.04	Low Absorption	High Resistance
30	Czechia	0.11	1.44	4.05	Low Absorption	High Resistance
31	Slovak Republic	0.11	1.51	3.89	Low Absorption	High Resistance
32	Colombia	0.10	1.54	3.80	Low Absorption	High Resistance
33	Hungary	0.10	1.52	3.85	Low Absorption	High Resistance
34	Costa Rica	0.09	1.55	3.76	Low Absorption	High Resistance
35	Estonia	0.08	1.58	3.68	Low Absorption	High Resistance
36	Lithuania	0.07	1.59	3.65	Low Absorption	High Resistance
37	Latvia	0.07	1.63	3.55	Low Absorption	High Resistance

The empirical estimates of technological absorption and resistance in Table 3 reveal significant variations across OECD economies, with certain expected leaders aligning closely with the global technological frontier. In contrast, others exhibit unexpected patterns of absorption and friction. While economies such as Switzerland, the United States, and the United Kingdom demonstrate both high levels of technological absorption and minimal internal resistance, others, including Japan and South Korea, do not rank as close to the technological frontier as might be expected. This divergence is shaped by structural, institutional, and sectoral factors that influence the pace and breadth of technological diffusion within each economy.

Switzerland displays strong levels of R&D within the private sector and has world-class education institutions, contributing to leading performances within science and technology (Hotz-Hart, 2011). These factors, alongside business-friendly intellectual property regulations, lead to breakthroughs and innovations. Switzerland also sources knowledge and technology from overseas to combine with its own developments to expand its current knowledge base (Hotz-Hart, 2011). A strong desire to lead advances in R&D domestically alongside seeking international knowledge solidifies Switzerland's first-place ranking. Naturally, Switzerland consistently ranks highly in the Global Innovation Index, placing first out of 133 economies for the last 14 years. Switzerland also ranks first in intellectual property payments and receipts as a percentage of total trade alongside university-industry R&D collaboration (World Intellectual Property Organisation, 2024).

A 2019 OECD report describes the United States as one of the countries accounting for the most developments at the digital technology frontier between 2013 and 2016. The United States is estimated to be at the forefront in developing several digital technologies, including aircraft traffic control alongside algorithms based on biological and mathematical models (OECD, 2019a). Investment in AI-related technologies and venture capital is also led by the United States (Brattberg et al., 2020). Academic institutions are keenly involved in conducting AI-related research while the private sector maintains an active role in integrating domestic and international research findings (Brattberg et al., 2020).

The United Kingdom is a global leader in the technological space, second only to the United States in ICT spending per capita (International Trade Administration, 2023). ICT spending is particularly large from financial services, utilities, and transportation companies. Furthermore, both central and local governments are conducting digital transformations as services are moved into online spaces, requiring strong ICT investment. London is the second most connected place for technology in the world, second only to Silicon Valley. The United Kingdom is also at the forefront of AI endeavours, displaying the third-largest AI market in the world (International Trade Administration, 2023).

Economic structures have significance in the adoption of technologies as developing nations have a low number of enterprises per worker that exhibit relative proximity to the technological frontier (Cirera et al., 2022). In many low-income countries, consumers lack access to digital technologies and the internet, reducing the need to utilise and develop digital platforms and technologies (Liu & Qiang, 2024). High-quality institutions are also vital in adopting technologies. Low-quality economic and financial institutions deplete incentives for investing in technologies, while low-quality political institutions reinforce barriers and risks, causing further delays to investment (Kiessling, 2007).

Sectoral factors are also important in the pace of technological adoption across countries. Of 14 surveyed countries, ICT goods, telecommunication, and IT services inputs are lowest in the agricultural sector, while the manufacturing sector has the highest share of ICT goods inputs, and modern services have the highest share of telecommunication and IT services inputs (Liu & Qiang, 2024). Therefore, countries with large agricultural sectors may see a slower pace and smaller breadth of technological diffusion relative to countries with a large manufacturing sector.

Institutional quality remains a key determinant of both technological absorption (DAI, $\boldsymbol{\rho}$) and technological resistance (CUFI, $\boldsymbol{u}$). Countries with strong legal frameworks, transparent regulatory environments, and efficient innovation ecosystems tend to integrate global technological advancements more effectively. A strong legal environment allows legislation to evolve proactively as new technologies emerge, allowing for more effective integration (such as proactive questions surrounding blockchain-based intellectual property management systems) and risk mitigation (Akpobome, 2024). Maintaining transparency is also vital in upholding trust in the digital economy (Llanos, 2021). Furthermore, a strong innovation ecosystem – as opposed to individual actors – contributes significantly to the development and implementation of disruptive innovations (Palmié et al., 2020). As displayed in the FinTech sector, emerging technologies were influenced through the direction of interdependent firms, ultimately growing into something revolutionary (Palmié et al., 2020).

Economies such as Switzerland, the United States, and Germany rank highly due to their stable business environments, strong intellectual property protections, and deep linkages between research institutions and industry (Swanek, 2021; World Intellectual Property Organization, 2024). These conditions facilitate continuous knowledge exchange and rapid adoption of emerging technologies across multiple sectors.

Australia and Germany stand out among the top-ranked countries due to their robust R&D ecosystems and strong industrial bases. Germany, known for its advanced manufacturing sector, excels in engineering, automotive technology, and industrial automation. The country benefits from close collaboration between universities, research institutions, and industry leaders, ensuring the continuous flow of innovation into production. Australia, with a high absorption index, leverages its strong university research system and advanced services sector, particularly in biotech, mining technology, and financial innovation. However, its geographical distance from major global innovation hubs may pose challenges to faster technology diffusion, particularly in advanced digital services.

Australia ranks highly in AI technologies, placing tenth in the world for AI readiness in 2024 (Oxford Insights, 2024). Quantum technology capabilities are also impressive, showing citations 60% higher than the global average (Donnellan, 2021). The Australian Government also incentivises R&D through tax incentive policies, encouraging businesses to invest in R&D (Department of Industry, Science and Resources, n.d.). Australia is also home to the Commonwealth Scientific and Industrial Research Organisation (CSIRO), which has a range of labs and facilities working on scientific research and technological innovation. These include the Pawsey Supercomputing Research Centre, National Vaccine Therapeutics Lab, and the Canberra Deep Space Communication Complex (CSIRO, 2025).

In 2023, 75% of German companies across most industries had implemented digital solutions (International Trade Administration, 2022). In 2021, Germany was ranked fourth for robot density in the world, with the motor vehicle industry installing the largest number of industrial robots (International Trade Administration, 2022). Furthermore, the automotive industry accounts for one-third of all R&D spending (Germany Trade & Invest, n.d.). Universities and other R&D institutes have a strong focus on Industry 4.0, digitalisation, and production technologies. Close collaboration with industry players promotes knowledge transfer, displaying Germany's strong ability to absorb technologies and champion innovation (Germany Trade & Invest, n.d.).

In contrast, economies that experience higher technological resistance often face institutional bottlenecks, regulatory inefficiencies, or structural rigidities that slow the adoption of global innovations. Countries such as Colombia, Latvia, and Costa Rica exhibit weaker institutional capacity, which hinders their ability to fully integrate technological spillovers into domestic production (Muizniece & Cepilovs, 2017; OECD, 2017; OECD, 2019b). These constraints manifest in delays to digital infrastructure development, limited access to venture capital for innovation, and slower adaptation to global technological standards.

When a country displays weak explicit and implicit institutions, this creates a roadblock in adopting new technologies (Suzuki, 2015). Explicit forms of institutions include government agency preparedness, incentive programmes, and regulations while implicit forms of institutions include information, awareness, and social acceptance (Suzuki, 2015). Inefficient regulation can sometimes have negative effects on the diffusion of innovations (Blind, 2012). For instance, effective product and consumer safety or product liability regulations increase acceptance of new innovations, leading to more diffusion and incentive to innovate (Blind, 2012). For countries with inefficient product and consumer safety or product liability regulations, the opposite effect can be expected.

However, the rankings of Japan and South Korea stand out as particularly unexpected, given their well-established reputations as technologically advanced economies. In 2024, Japan ranked 13th overall in the WIPO Global Innovation Index and 8th for ICT infrastructure, while South Korea ranked both 6th both overall and for ICT infrastructure (World Intellectual Property Organisation, 2024). Japan has a strong focus on advanced manufacturing technologies, including automation, Industry 4.0 solutions, and robotics (International Trade Administration, 2025). In 2023, 38% of all industrial robots originated from Japan (International Trade Administration, 2025). On the other hand, Korea delivers world-class key technologies, including semiconductors, 6G, and ICT infrastructure (OECD, 2023a). Korea also has the second-highest R&D expenditure in the OECD. For example, in 2019, the Korean manufacturing sector spent 56% of R&D expenditure on electronic components, computers, visual, sound, and communication equipment (OECD, 2023a).

Although Japan and South Korea have globally competitive high-tech industries, their technological absorption and friction rankings suggest structural factors that moderate the diffusion of frontier technologies across their economies. One of the primary reasons for this outcome may be the role of domestic technological resistance in shaping their absorption capacities. There is a heavy reliance on large corporations to deliver innovation through internal R&D processes in Japan, resulting in a lack of start-ups (Stewart, 2023). Japanese technology markets – unlike the United States – are consistently dominated by the same firms as opposed to innovative new entrants (Rtischev & Cole, 2003). Breaking into the strongly established Japanese high technology market is also seen to have a higher cost (Rtischev & Cole, 2003). In South Korea, technological adoption is strong among large conglomerates; however, small and medium-sized enterprises (SMEs) remain sluggish in technological uptake (OECD, 2023a). This effect is seen due to large enterprises attracting the most talented employees with better working conditions alongside a digital skills gap among older workers (OECD, 2023a).

Despite substantial investments in R&D and industrial automation in Japan, adopting digital and platform-based technologies may have progressed more slowly than in other advanced economies. This may be due to corporate conservatism, deeply embedded hierarchical decision-making structures, and legacy industrial infrastructure, which could have hindered the shift toward disruptive, data-driven innovations. For instance, 80% of ICT expenditure is targeted towards maintaining legacy systems (Kawai, 2023). Furthermore, many Japanese citizens dismiss technological solutions in favour of the centuries-old hanko system, where unique physical seals are used in place of a signature alongside using offline physical media (Kawai, 2023).

While Japan remains a global leader in advanced manufacturing, robotics, and automotive technology, the broader diffusion of digital transformation across industries may have been more gradual, particularly in sectors such as financial technology, e-commerce, and cloud-based services. Fintech uptake is significantly underdeveloped in Japan, relative to other countries (Iwashita, 2022). Japan's banking industry is dominated by face-to-face branch banking practices as the cash-to-nominal GDP ratio exceeded 20% in 2021, and elderly citizens in particular prefer to keep large sums of cash in their houses (Iwashita, 2022). Compared to other OECD countries, Japan underperforms in the share of businesses purchasing cloud services, ranking 34th where only 24.1% of businesses with ten or more employees purchased cloud services in 2024 (OECD, n.d.-a.). E-commerce participation is also below the OECD average, ranking 26th as only 72% of citizens aged 16-74 had purchased online in 2023 (OECD, n.d.-b).

A similar pattern is observed in South Korea, where the technological frontier is largely driven by a few dominant conglomerates (chaebols) such as Samsung, Hyundai, and LG. For instance, the proportion of large innovating firms (500+ employees) is five times larger than the number of small innovating firms (10-49 employees) (OECD, 2023a). In countries like Germany, this proportion is closer to 23.4%. Furthermore, Korea's ten largest chaebols accounted for 47% of all R&D expenditure in 2019, while R&D growth was led by the four largest chaebols (OECD, 2023a). These firms operate at the cutting edge of technological innovation in semiconductors, consumer electronics, and automotive technology. However, technology diffusion beyond these large corporations is less efficient, resulting in an uneven distribution of technological adoption across the broader economy. The largest barrier to technological diffusion among SMEs is a lack of information regarding new technologies, resulting in low trust (Pak, 2021). Furthermore, SMEs – which constitute a substantial portion of South Korea's industrial landscape – often struggle to keep pace with the rapid technological advancements of chaebols due to limited access to capital, R&D networks, and skilled digital talent (Pak, 2021). This dynamic creates internal technological resistance despite the country's leadership in select high-tech sectors.

The Technological Component values in Table 3 reinforce these findings, measuring how technological progress contributes to economic output. Given that real GDP per capita has been standardised by its geometric mean, this component reflects each country's relative technological standing in terms of productivity gains derived from technology adoption. While Switzerland (5.52) and the United States (5.50) score highly, indicating that technological progress plays a strong role in driving economic output, Japan (5.13) and South Korea (4.61) show lower values than expected, suggesting that their technological advancements are concentrated within specific industries rather than being widely diffused across the economy. In contrast, economies such as Colombia (3.80), Costa Rica (3.76), and Latvia (3.55), which exhibit both low absorption (DAI) and high internal friction (CUFI), also have some of the lowest Technological Component values further confirming the existence of significant barriers to productivity-enhancing technology diffusion.

The sectoral composition of these economies further explains their moderate absorption scores. While Japan and South Korea maintain strong industrial and manufacturing bases, their reliance on incremental innovation in well-established industries rather than rapid adoption of frontier technologies in digital services, artificial intelligence, and cloud computing has affected their positioning relative to other advanced countries (Iwashita, 2022; OECD, n.d.-a; Pak, 2021). For instance, Switzerland and the United States emphasise highly scalable, disruptive innovations in finance, artificial intelligence, and digital transformation, maintain higher levels of absorption and lower internal friction, ranking tenth and seventh in worldwide knowledge absorption, respectively (World Intellectual Property Organization, 2024).

Demographic and labour market dynamics are another important factor influencing technological absorption and resistance. Both Japan and South Korea face ageing populations, which impact labour market flexibility and skill transition. Japan faces one of the most rapidly ageing populations in the world, with over 30% of the population over 65 (Müller, 2024). As older workers continue to participate in the labour market, upskilling is crucial to adapt to evolving job requirements. However, a myriad of socioeconomic, cultural, and structural barriers impedes older people from participating in training programmes, resulting in a large workforce preparedness gap (Müller, 2024). Korea faces a similar environment, where 20% of the population is over 65 years old (Seo & Lau, 2024). Upon introducing new technologies, Korean firms require task reallocation, which may reduce the quality of matching between jobs and workers, particularly for older workers (Chung & Lee, 2023). This suggests firms with a higher proportion of older workers will have greater difficulty introducing new innovations. Furthermore, older workers in the manufacturing sector were more likely to retire following the introduction of new technologies relative to younger workers (Chung & Lee, 2023).

While automation and robotics have been extensively integrated into industrial production, their diffusion into service sectors, small businesses, and digital industries has been more constrained. The high degree of specialisation in industrial production, particularly in Japan, may have contributed to strong technological leadership in niche areas, but with slower, economy-wide technological diffusion compared to more flexible innovation ecosystems in economies such as the United States and Switzerland.

Beyond institutional and sectoral factors, public policy interventions significantly influence both the level of technological absorption and the degree of internal friction within an economy. Well-designed policy can enhance incentives for technological adoption – thereby increasing productivity – alongside creating an environment where the most productive firms are reallocated resources

(Andrews et al., 2015). This includes policies regarding well-functioning product markets, labour markets, risk capital markets, and bankruptcy laws where failure is not penalised excessively (Andrews et al., 2015).

Countries that have actively designed policies to foster broad-based innovation ecosystems exhibit higher absorption rates and lower technological resistance. France, Ireland, and Norway have developed national strategies focused on R&D investment, digital transformation, and startup acceleration, creating an environment that facilitates technological diffusion beyond large corporations and across multiple industries. In contrast, economies where government support for innovation remains fragmented or disproportionately concentrated in specific industries exhibit higher resistance to global technological diffusion. In the case of Japan and South Korea, innovation policies have traditionally favoured industrial champions, which has resulted in strong technological capabilities within certain sectors but limited diffusion across the broader economy. These findings suggest that even highly innovative economies can experience technological bottlenecks when innovation is concentrated within specific sectors or dominant firms rather than being widely distributed across the entire economy. The positioning of Japan and South Korea within the middle-absorption, medium-resistance category highlights the complexity of technological adoption beyond traditional innovation metrics.

The broader global positioning of OECD economies in terms of technological adoption and friction reveals distinct patterns of divergence. High-absorption, low-resistance economies, such as Switzerland, the United States, and the United Kingdom, maintain continuous integration of new technologies with minimal internal constraints. These countries are net exporters of innovation, benefiting from strong institutional frameworks, high workforce digital literacy, and supportive policy environments. This is reflected through the 2024 Global Innovation Index, where Switzerland ranks first, the United States ranks third, and the United Kingdom ranks fifth (World Intellectual Property Organisation, 2024). These rankings are influenced by strong institutions, human capital, research, infrastructure, market sophistication, business sophistication, knowledge and technology outputs, and creative outputs (World Intellectual Property Organisation, 2024). In contrast, economies such as France, Japan, and Ireland, which occupy a middle position in technological absorption and friction, demonstrate moderate integration capabilities but still experience regulatory or structural barriers that slow the diffusion of frontier technologies.

At the lower end of the absorption spectrum, economies such as Colombia, Costa Rica, and Latvia struggle with both low technological absorption and high internal resistance. These countries face persistent structural challenges that limit their ability to fully leverage external technological spillovers, resulting in slower convergence with frontier economies. For instance, Colombia faces challenges in finding skilled technical workers as enrolment in professional and technical degrees remains low, leading to low-quality managerial oversight, further limiting technological adoption (OECD, 2019b). Additionally, a lack of competitive pressures alongside high rates of family-controlled firms and informal employment arrangements impede the adoption of technologies in Colombia (OECD, 2019b). Costa Rica's innovation system displays low levels of investment in R&D and technology adoption, resulting in weak absorptive capabilities in the domestic business sector (OECD, 2017). This is further exacerbated by weak linkages between industries and academia (OECD, 2017). Similar to Colombia, Latvia has a shortage of skilled workers, impeding the country's ability to adopt technological innovations (Yashiro et al., 2019).

Weak institutional frameworks, lower investment in R&D, and constrained digital infrastructure contribute to the persistence of technological gaps, reinforcing long-term productivity differentials across OECD economies. Technological change is facilitated through financial and government institutions, among others (UNCTAD, 2021). Strong financial institutions are important during the introduction stage of new technologies, while strong economic institutions are most important as technologies shift towards mainstream adoption (Kiessling, 2007). On the other hand, the government facilitates technological change through policies, rules, and regulations (UNCTAD, 2021).

Furthermore, enhancing technological capabilities through R&D helps lagging countries catch up to frontier countries faster. Infrastructure is also vital as frontier countries depend on high-speed internet connections, while many developing countries do not have the necessary digital infrastructure to catch up (UNCTAD, 2021).

Chapter 6 – Concluding remarks

The results underscore the multifaceted nature of technological absorption and resistance, emphasising that economic performance and innovation potential are shaped not only by technological capabilities at the industry level but also by the broader institutional, labour market, and policy factors. The capacity of an economy to integrate global technological advancements efficiently depends not only on external exposure to frontier technologies but also on domestic conditions that facilitate or hinder widespread adoption. The empirical estimates provide a systematic framework for understanding the relative positioning of OECD economies within the global technological landscape and highlight the key factors that shape their ability to compete in an increasingly technology-driven world.

The long-run technological trajectory of a country is determined by the Direct Absorption Index (DAI) and the Catch-Up Friction Index (CUFI). Empirical results estimate that countries such as Switzerland, the United States, and the United Kingdom are closely aligned with the global technological frontier while also exhibiting low internal resistance. On the other hand, countries such as Colombia, Costa Rica, and Latvia are positioned relatively far away from the global technological frontier while facing high levels of internal resistance.

These positions are determined by a myriad of country-specific institutional, sectoral, and structural factors. For instance, Switzerland's world-class educational institutions and strong R&D efforts, the United States' strong AI investments and integration of international findings, and the United Kingdom's widespread use of ICT in financial services and large AI market have propelled these countries to closely align with the global technological frontier. Conversely, Colombia's lack of competitive pressures and high rates of informal employment, Costa Rica's low investment in R&D and technology adoption, and Latvia's shortage of skilled workers have resulted in poor alignment with the global technological frontier.

Lower levels of absorption and higher levels of resistance can also arise due to cultural factors, as seen from Japan's dismissal of technological solutions in e-commerce, finance, and cloud-based services. Reliance on well-established industries and conglomerates also impedes technological absorption, as seen in both Japan and South Korea.

Ultimately, technological absorption and internal friction can be influenced by effectively designed public policy, and technological gaps can narrow through optimising structural, institutional, and sectoral factors.

This research could be expanded in the future to analyse countries outside of the OECD with a reputation for strong technological innovation, such as China and Singapore. For instance, Singapore ranked 4^{th} overall and China ranked 11^{th} overall in the 2024 Global Innovation Index (World Intellectual Property Organisation, 2024). Additionally, a more in-depth analysis of domestic regions in countries such as Japan and South Korea could provide more insight into the nuances of their positions relative to the global technological frontier.

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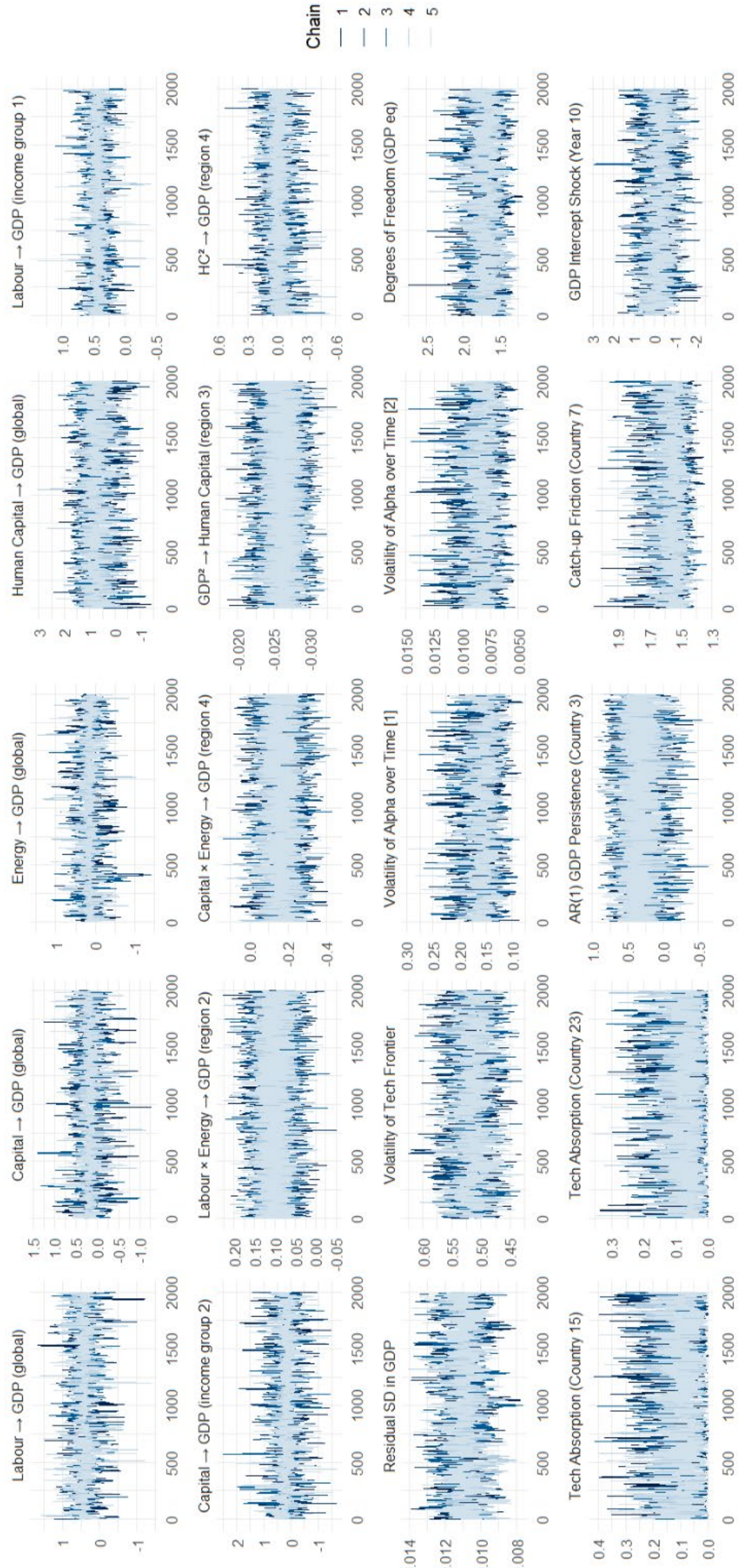
Appendices

Appendix A1

Trace Plots of Selected Posterior Parameters



Appendix A2

Posterior Means, Standard Deviations, and 90% Credible Intervals for the Hierarchical Specification

Parameter	Posterior Mean	Standard Deviation	90% credible interval
GDP equation			
α_Y *(global constant)*	-4.67	0.285	[-5.11, -4.20]
σ_{υ_Y} *(global scale)*	0.011	0.001	[0.009, 0.013]
σ_τ *(scale of latent technology)*	0.522	0.027	[0.478, 0.568]
σ_τ^o *(scale of observed technology*	0.002	0.001	[0.001, 0.003]
$\sigma_{\alpha_{t,Y}}$ *(scale of time effects)*	0.164	0.033	[0.117, 0.226]
υ_Y *(degrees of freedom)*	1.70	0.181	[1.44, 2.03]
Region-based elasticities			
Oceania			
$\beta_{\log(labour)}$	0.417	0.160	[0127, 0.661]
$\beta_{log(capital)}$	0.13	0.053	[0.041, 0.216]
$\beta_{log(energy)}$	0.131	0.084	[-0.022, 0.249]
$\beta_{log\ (labour)^2}$	0.775	1.656	[-0.407, 1.66]
$\beta_{log\ (capital)^2}$	-0.015	0.045	[-0.09, 0.059]
$\beta_{log\ (energy)^2}$	-0.706	0.276	[-1.13, -0.229]
$\beta_{\log\ (labour) \times log(capital)}$	-0.258	0.207	[-0.614, 0.066]
$\beta_{\log\ (labour) \times log(energy)}$	-0.174	0.371	[-0.787, 0.429]
$\beta_{\log\ (capital) \times log(energy)}$	-0.031	0.073	[-0.141, 0.097]
$\gamma_{\log(human\ capital)}$	0.056	0.112	[-0.102, 0.259]
$\gamma_{log\ (human\ capital)^2}$	-0.006	0.099	[-0.176, 0.152]
$\gamma_{log\ (human\ capital),t-1}$	-0.004	0.089	[-0.153, 0.142]
Europe			
$\beta_{\log(labour)}$	0.465	0.048	[0.386, 0.543]
$\beta_{log(capital)}$	0.23	0.011	[0.21, 0.246]
$\beta_{log(energy)}$	0.144	0.021	[0.109, 0.18]
$\beta_{log\ (labour)^2}$	1.08	0.257	[0.658, 1.5]
$\beta_{log\ (capital)^2}$	-0.033	0.006	[-0.043, -0.022]
$\beta_{log\ (energy)^2}$	0.099	0.036	[0.04, 0.158]
$\beta_{\log\ (labour) \times log(capital)}$	0.059	0.026	[0.015, 0.101]
$\beta_{\log\ (labour) \times log(energy)}$	-0.555	0.066	[-0.663, -0.446]
$\beta_{\log\ (capital) \times log(energy)}$	-0.014	0.009	[-0.029, 0.001]
$\gamma_{\log(human\ capital)}$	0.061	0.101	[-0.073, 0.254]
$\gamma_{log\ (human\ capital)^2}$	-0.018	0.109	[-0.206, 0.147]
$\gamma_{log\ (human\ capital),t-1}$	-0.022	0.067	[-0.138, 0.083]
Americas			
$\beta_{\log(labour)}$	0.354	0.108	[0.163, 0.513]
$\beta_{log(capital)}$	0.19	0.027	[0.146, 0.234]
$\beta_{log(energy)}$	0.148	0.052	[0.066, 0.235]
$\beta_{log\ (labour)^2}$	0.526	0.658	[-0.71, 1.39]
$\beta_{log\ (capital)^2}$	0.037	0.017	[0.01, 0.064]
$\beta_{log\ (energy)^2}$	-0.106	0.053	[-0.193, -0.022]
$\beta_{\log\ (labour) \times log(capital)}$	0.193	0.077	[0.066, 0.32]
$\beta_{\log\ (labour) \times log(energy)}$	0.28	0.108	[0.108, 0.46]

$\beta_{\log(capital)\times log(energy)}$	-0.066	0.015	[-0.09, -0.043]
$\gamma_{\log(human\ capital)}$	0.063	0.116	[-0.091, 0.279]
$\gamma_{log\ (human\ capital)^2}$	-0.007	0.102	[-0.183, 0.149]
$\gamma_{log\ (human\ capital),t-1}$	0.000	0.076	[-0.128, 0.126]
Asia			
$\beta_{\log(labour)}$	0.494	0.11	[0.329, 0.69]
$\beta_{log(capital)}$	0.259	0.036	[0.202, 0.319]
$\beta_{log(energy)}$	0.163	0.044	[0.010, 0.244]
$\beta_{log\ (labour)^2}$	0.882	0.491	[0.031, 1.63]
$\beta_{log\ (capital)^2}$	0.053	0.027	[0.007, 0.098]
$\beta_{log\ (energy)^2}$	0.327	0.142	[0.099, 0.562]
$\beta_{\log(labour)\times log(capital)}$	-0.153	0.08	[-0.284, -0.02]
$\beta_{\log(labour)\times log(energy)}$	0.075	0.263	[-0.347, 0.509]
$\beta_{\log(capital)\times log(energy)}$	-0.120	0.034	[-0.174, -0.064]
$\gamma_{\log(human\ capital)}$	0.152	0.149	[-0.016, 0.449]
$\gamma_{log\ (human\ capital)^2}$	-0.007	0.102	[-0.183, 0.149]
$\gamma_{log\ (human\ capital),t-1}$	0.035	0.089	[-0.093, 0.20]
Scale			
$\sigma^{r}_{\gamma_{H\to Y}}$	0.061	0.043	[0.003, 0.14]
$\sigma^{region}_{\log(\mathrm{labour})}$	0.162	0.142	[0.012, 0.431]
$\sigma^{region}_{\log(capital)}$	0.111	0.103	[0.021, 0.296]
$\sigma^{region}_{\log(energy)}$	0.072	0.084	[0.004, 0.23]
$\sigma^{region}_{(log\ (labour))^2}$	0.429	0.292	[0.036, 0.973]
$\sigma^{region}_{(log\ (capital))^2}$	0.087	0.066	[0.027, 0.217]
$\sigma^{region}_{(log\ (energy))^2}$	0.525	0.214	[0.246, 0.929]
$\sigma^{region}_{log(labour)\times log(capital)}$	0.298	0.164	[0.103, 0.614]
$\sigma^{region}_{log(labour)\times log(energy)}$	0.486	0.207	[0.234, 0.898]
$\sigma^{region}_{log(capital)\times log(energy)}$	0.11	0.092	[0.029, 0.283]
Human Capital equation			
Region-based elasticities			
α_H *(global constant)*	0.011	0.003	[0.006, 0.015]
σ_{υ_H} *(global scale)*	0.009	0.001	[0.008, 0.01]
$\sigma_{\alpha_{t,H}}$ *(scale of time effects)*	0.009	0.002	[0.006, 0.012]
υ_H *(degrees of freedom)*	3.67	0.612	[2.78, 4.77]
Oceania			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.032	0.016	[0.005, 0.058]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.014	0.017	[-0.041, 0.013]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	0.012	0.014	[-0.010, 0.036]
Europe			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.036	0.002	[0.032, 0.040]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.029	0.002	[-0.032, -0.026]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	0.012	0.003	[0.008, 0.017]
Americas			
$\gamma_{\log(real\ gdp\ per\ capita)}$	-0.001	0.004	[-0.008, 0.006]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.026	0.002	[-0.029, -0.023]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	-0.001	0.003	[-0.006, 0.003]
Asia			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.089	0.009	[0.073, 0.104]

$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	0.023	0.007	[0.012, 0.034]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	-0.005	0.005	[-0.014, 0.004]
Scale			
$\sigma^{r}_{\gamma_{Y\to H}}$	0.031	0.008	[0.020, 0.046]
GDP equation			
Income-based elasticities			
Advanced Economy			
$\beta_{\log(labour)}$	0.423	0.13	[0.209, 0.598]
$\beta_{log(capital)}$	0.204	0.08	[0.09, 0.304]
$\beta_{log(energy)}$	0.144	0.062	[0.055, 0.23]
$\beta_{log\ (labour)^2}$	0.765	0.442	[-0.042, 1.39]
$\beta_{log\ (capital)^2}$	0.014	0.056	[-0.065, 0.10]
$\beta_{log\ (energy)^2}$	-0.09	0.271	[-0.542, 0.339]
$\beta_{\log\ (labour)\times log(capital)}$	-0.048	0.179	[-0.353, 0.224]
$\beta_{\log\ (labour)\times log(energy)}$	-0.065	0.287	[-0.503, 0.419]
$\beta_{\log\ (capital)\times log(energy)}$	-0.064	0.075	[-0.169, 0.042]
$\gamma_{\log(human\ capital)}$	0.063	0.088	[-0.024, 0.247]
$\gamma_{log\ (human\ capital)^2}$	-0.008	0.069	[-0.132, 0.096]
$\gamma_{log\ (human\ capital),t-1}$	0.001	0.050	[-0.084, 0.086]
Emerging Economy			
$\beta_{\log(labour)}$	0.397	0.352	[-0.175, 0.954]
$\beta_{log(capital)}$	0.186	0.368	[-0.456, 0.738]
$\beta_{log(energy)}$	0.157	0.303	[-0.329, 0.661]
$\beta_{log\ (labour)^2}$	0.745	0.541	[-0.205, 1.57]
$\beta_{log\ (capital)^2}$	0.055	0.324	[-0.418, 0.602]
$\beta_{log\ (energy)^2}$	-0.098	0.435	[-0.795, 0.583]
$\beta_{\log\ (labour)\times log(capital)}$	-0.023	0.39	[-0.655, 0.636]
$\beta_{\log\ (labour)\times log(energy)}$	-0.033	0.464	[-0.727, 0.777]
$\beta_{\log\ (capital)\times log(energy)}$	-0.053	0.334	[-0.559, 0.511]
$\gamma_{\log(human\ capital)}$	-0.002	0.065	[-0.107, 0.104]
$\gamma_{log\ (human\ capital)^2}$	-0.001	0.063	[-0.106, 0.10]
$\gamma_{log\ (human\ capital),t-1}$	0.001	0.065	[-0.109, 0.105]
Scale			
$\sigma^{j}_{\gamma_{H\to Y}}$	0.055	0.037	[0.006, 0.126]
$\sigma^{income}_{\log(\text{labour})}$	0.201	0.143	[0.02, 0.475]
$\sigma^{income}_{\log(capital)}$	0.209	0.145	[0.026, 0.484]
$\sigma^{income}_{\log(energy)}$	0.184	0.14	[0.014, 0.455]
$\sigma^{income}_{(log\ (labour))^2}$	0.197	0.15	[0.017, 0.481]
$\sigma^{income}_{(log\ (capital))^2}$	0.182	0.152	[0.007, 0.48]
$\sigma^{income}_{(log\ (energy))^2}$	0.199	0.146	[0.018, 0.475]
$\sigma^{income}_{log(labour)\times log(capital)}$	0.207	0.148	[0.019, 0.489]
$\sigma^{income}_{log(labour)\times log(energy)}$	0.203	0.149	[0.018, 0.485]
$\sigma^{income}_{log(capital)\times log(energy)}$	0.198	0.147	[0.012, 0.481]
Human Capital equation			
Income-based elasticities			
Advanced Economy			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.024	0.017	[-0.003, 0.053]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.007	0.013	[-0.029, 0.014]

$\gamma_{log\,(real\,gdp\,per\,capita),t-1}$	0.004	0.012	[-0.014, 0.025]
Emerging Economy			
$\gamma_{\log(real\,gdp\,per\,capita)}$	-0.001	0.031	[-0.051, 0.047]
$\gamma_{log\,(real\,gdp\,per\,capita)^2}$	0.00	0.031	[-0.05, 0.048]
$\gamma_{log\,(real\,gdp\,per\,capita),t-1}$	0.00	0.031	[-0.046, 0.046]
Scale			
$\sigma^j_{\gamma_{Y\to H}}$	0.026	0.018	[0.005, 0.063]

Appendix A3

Posterior Means, Standard Deviations, and 90 % Credible Intervals for the Income (Advanced/Emerging countries) Specification

Parameter	Posterior Mean	Standard Deviation	90% credible interval
GDP equation			
α_Y *(global constant)*	-4.86	0.293	[-5.36, -4.39]
σ_{υ_Y} *(global scale)*	0.012	0.001	[0.01, 0.013]
σ_τ *(scale of latent technology)*	0.529	0.028	[0.484, 0.577]
σ_τ^O *(scale of observed technology*	0.001	0.001	[0.001, 0.003]
$\sigma_{\alpha_{t,Y}}$ *(scale of time effects)*	0.124	0.025	[0.087, 0.169]
υ_Y *(degrees of freedom)*	1.69	0.18	[1.42, 2.01]
GDP equation			
Income-based elasticities			
Advanced Economy			
$\beta_{\log(labour)}$	0.456	0.056	[0.363, 0.548]
$\beta_{log(capital)}$	0.14	0.01	[0.123, 0.157]
$\beta_{log(energy)}$	0.175	0.024	[0.135, 0.214]
$\beta_{log\,(labour)^2}$	-0.327	0.33	[-0.87, 0.204]
$\beta_{log\,(capital)^2}$	-0.013	0.004	[-0.019, -0.006]
$\beta_{log\,(energy)^2}$	0.131	0.042	[0.061, 0.199]
$\beta_{\log\,(labour)\times log(capital)}$	0.044	0.026	[0.001, 0.087]
$\beta_{\log\,(labour)\times log(energy)}$	-0.441	0.082	[-0.575, -0.306]
$\beta_{\log\,(capital)\times log(energy)}$	-0.026	0.008	[-0.04, -0.012]
$\gamma_{\log(human\,capital)}$	-0.039	0.085	[-0.203, 0.076]
$\gamma_{log\,(human\,capital)^2}$	-0.002	0.084	[-0.143, 0.138]
$\gamma_{log\,(human\,capital),t-1}$	-0.089	0.101	[-0.286, 0.023]
Emerging Economy			
$\beta_{\log(labour)}$	0.373	0.098	[0.202, 0.522]
$\beta_{log(capital)}$	0.273	0.03	[0.223, 0.321]
$\beta_{log(energy)}$	0.197	0.058	[0.108, 0.299]
$\beta_{log\,(labour)^2}$	-1.66	0.723	[-2.83, -0.474]
$\beta_{log\,(capital)^2}$	0.006	0.013	[-0.015, 0.029]
$\beta_{log\,(energy)^2}$	-0.028	0.074	[-0.147, 0.098]
$\beta_{\log\,(labour)\times log(capital)}$	0.152	0.064	[0.048, 0.258]
$\beta_{\log\,(labour)\times log(energy)}$	0.52	0.12	[0.322, 0.72]
$\beta_{\log\,(capital)\times log(energy)}$	-0.044	0.022	[-0.081, -0.01]
$\gamma_{\log(human\,capital)}$	0.095	0.107	[-0.024, 0.307]
$\gamma_{log\,(human\,capital)^2}$	-0.011	0.084	[-0.155, 0.119]
$\gamma_{log\,(human\,capital),t-1}$	0.006	0.056	[-0.084, 0.105]
Scale			
$\sigma^j_{\gamma_{H\to Y}}$	0.073	0.044	[0.007, 0.148]
$\sigma^{income}_{\log(\text{labour})}$	0.152	0.12	[0.012, 0.387]
$\sigma^{income}_{\log(capital)}$	0.184	0.117	[0.053, 0.415]
$\sigma^{income}_{\log(energy)}$	0.12	0.117	[0.007, 0.362]
$\sigma^{income}_{(log\,(labour))^2}$	0.473	0.206	[0.099, 0.799]
$\sigma^{income}_{(log\,(capital))^2}$	0.094	0.103	[0.005, 0.314]
$\sigma^{income}_{(log\,(energy))^2}$	0.192	0.124	[0.036, 0.432]

$\sigma^{income}_{log(labour) \times log(capital)}$	0.162	0.12	[0.023, 0.397]
$\sigma^{income}_{log(labour) \times log(energy)}$	0.426	0.125	[0.248, 0.656]
$\sigma^{income}_{log(capital) \times log(energy)}$	0.091	0.10	[0.004, 0.302]
Human Capital equation			
α_H *(global constant)*	0.019	0.004	[0.013, 0.025]
σ_{υ_H} *(global scale)*	0.007	0.000	[0.007, 0.008]
$\sigma_{\alpha_{t,H}}$ *(scale of time effects)*	0.012	0.002	[0.009, 0.015]
υ_H *(degrees of freedom)*	2.60	0.361	[2.07, 3.24]
Income-based elasticities			
Advanced Economy			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.009	0.005	[0.002, 0.017]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.004	0.003	[-0.008, 0.000]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	0.001	0.004	[-0.006, 0.008]
Emerging Economy			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.128	0.007	[0.116, 0.139]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	0.05	0.005	[0.042, 0.058]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	0.001	0.002	[-0.003, 0.005]
Scale			
$\sigma^j_{\gamma_{Y \to H}}$	0.06	0.016	[0.038, 0.09]

Appendix A4

Posterior Means, Standard Deviations, and 95 % Credible Intervals for the Region Based Specification

Parameter	Posterior Mean	Standard Deviation	90% credible interval
GDP equation			
α_Y *(global constant)*	-4.62	0.282	[-5.1, -4.18]
σ_{υ_Y} *(global scale)*	0.011	0.001	[0.01, 0.012]
σ_τ *(scale of latent technology)*	0.516	0.028	[0.472, 0.562]
σ_τ^o *(scale of observed technology*	0.002	0.000	[0.000, 0.003]
$\sigma_{\alpha_{t,Y}}$ *(scale of time effects)*	0.161	0.029	[0.121, 0.213]
υ_Y *(degrees of freedom)*	1.69	0.18	[1.42, 2.01]
Region-based elasticities			
Oceania			
$\beta_{\log(labour)}$	0.428	0.158	[0.16, 0.677]
$\beta_{log(capital)}$	0.127	0.052	[0.038, 0.21]
$\beta_{log(energy)}$	0.125	0.088	[-0.047, 0.242]
$\beta_{log\ (labour)^2}$	0.772	0.676	[-0.455, 1.72]
$\beta_{log\ (capital)^2}$	-0.011	0.045	[-0.085, 0.063]
$\beta_{log\ (energy)^2}$	-0.684	0.294	[-1.14, -0.153]
$\beta_{\log\ (labour)\times log(capital)}$	-0.272	0.202	[-0.619, 0.041]
$\beta_{\log\ (labour)\times log(energy)}$	-0.179	0.386	[-0.824, 0.45]
$\beta_{\log\ (capital)\times log(energy)}$	-0.028	0.074	[-0.135, 0.106]
$\gamma_{\log(human\ capital)}$	-0.008	0.076	[-0.137, 0.108]
$\gamma_{log\ (human\ capital)^2}$	0.000	0.076	[-0.124, 0.128]
$\gamma_{log\ (human\ capital),t-1}$	-0.005	0.076	[-0.134, 0.116]
Europe			
$\beta_{\log(labour)}$	0.466	0.048	[0.386, 0.544]
$\beta_{log(capital)}$	0.23	0.011	[0.211, 0.247]
$\beta_{log(energy)}$	0.145	0.021	[0.11, 0.181]
$\beta_{log\ (labour)^2}$	1.08	0.258	[0.66, 1.51]
$\beta_{log\ (capital)^2}$	-0.033	0.006	[-0.043, -0.022]
$\beta_{log\ (energy)^2}$	0.101	0.035	[0.043, 0.158]
$\beta_{\log\ (labour)\times log(capital)}$	0.06	0.026	[0.017, 0.103]
$\beta_{\log\ (labour)\times log(energy)}$	-0.558	0.066	[-0.667, -0.449]
$\beta_{\log\ (capital)\times log(energy)}$	-0.014	0.009	[-0.029, 0.000]
$\gamma_{\log(human\ capital)}$	0.008	0.066	[-0.095, 0.125]
$\gamma_{log\ (human\ capital)^2}$	-0.012	0.078	[-0.149, 0.104]
$\gamma_{log\ (human\ capital),t-1}$	-0.02	0.056	[-0.124, 0.061]
Americas			
$\beta_{\log(labour)}$	0.362	0.104	[0.176, 0.515]
$\beta_{log(capital)}$	0.187	0.026	[0.144, 0.228]
$\beta_{log(energy)}$	0.148	0.051	[0.066, 0.236]
$\beta_{log\ (labour)^2}$	0.462	0.701	[-0.88, 1.35]
$\beta_{log\ (capital)^2}$	0.034	0.016	[0.007, 0.061]
$\beta_{log\ (energy)^2}$	-0.107	0.052	[-0.193, -0.024]
$\beta_{\log\ (labour)\times log(capital)}$	0.203	0.079	[0.073, 0.331]
$\beta_{\log\ (labour)\times log(energy)}$	0.289	0.111	[0.11, 0.477]

$\beta_{\log(capital)\times log(energy)}$	-0.068	0.015	[-0.093, -0.043]
$\gamma_{\log(human\ capital)}$	0.000	0.077	[-0.125, 0.124]
$\gamma_{log\ (human\ capital)^2}$	-0.003	0.078	[-0.13, 0.124]
$\gamma_{log\ (human\ capital),t-1}$	-0.006	0.066	[-0.12, 0.10]
Asia			
$\beta_{\log(labour)}$	0.488	0.108	[0.327, 0.677]
$\beta_{log(capital)}$	0.261	0.035	[0.205, 0.319]
$\beta_{log(energy)}$	0.163	0.044	[0.098, 0.244]
$\beta_{log\ (labour)^2}$	0.846	0.506	[-0.069, 1.62]
$\beta_{log\ (capital)^2}$	0.054	0.028	[0.007, 0.098]
$\beta_{log\ (energy)^2}$	0.321	0.147	[0.078, 0.559]
$\beta_{\log(labour)\times log(capital)}$	-0.161	0.081	[-0.292, -0.025]
$\beta_{\log(labour)\times log(energy)}$	0.099	0.278	[-0.338, 0.577]
$\beta_{\log(capital)\times log(energy)}$	-0.12	0.033	[-0.173, -0.065]
$\gamma_{\log(human\ capital)}$	0.097	0.13	[-0.022, 0.369]
$\gamma_{log\ (human\ capital)^2}$	0.002	0.075	[-0.12, 0.125]
$\gamma_{log\ (human\ capital),t-1}$	0.038	0.08	[-0.06, 0.194]
Scale			
$\sigma^{r}_{\gamma_{H\to Y}}$	0.063	0.043	[0.006, 0.145]
$\sigma^{region}_{\log(\mathrm{labour})}$	0.155	0.145	[0.011, 0.43]
$\sigma^{region}_{\log(capital)}$	0.112	0.095	[0.026, 0.289]
$\sigma^{region}_{\log(energy)}$	0.073	0.089	[0.004, 0.245]
$\sigma^{region}_{(log\ (labour))^2}$	0.444	0.301	[0.048, 1.01]
$\sigma^{region}_{(log\ (capital))^2}$	0.089	0.073	[0.027, 0.225]
$\sigma^{region}_{(log\ (energy))^2}$	0.499	0.217	[0.202, 0.908]
$\sigma^{region}_{log(labour)\times log(capital)}$	0.315	0.168	[0.114, 0.642]
$\sigma^{region}_{log(labour)\times log(energy)}$	0.495	0.194	[0.247, 0.859]
$\sigma^{region}_{log(capital)\times log(energy)}$	0.105	0.086	[0.03, 0.264]

Human Capital equation

Region-based elasticities			
α_H *(global constant)*	0.011	0.003	[0.006, 0.015]
σ_{υ_H} *(global scale)*	0.009	0.000	[0.008, 0.01]
$\sigma_{\alpha_{t},H}$ *(scale of time effects)*	0.008	0.001	[0.006, 0.011]
υ_H *(degrees of freedom)*	3.70	0.655	[2.81, 4.89]
Oceania			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.025	0.016	[0.000, 0.051]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.009	0.017	[-0.037, 0.02]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	0.015	0.014	[-0.008, 0.039]
Europe			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.036	0.003	[0.032, 0.04]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.029	0.002	[-0.032, -0.026]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	0.012	0.003	[0.008, 0.017]

Americas			
$\gamma_{\log(real\ gdp\ per\ capita)}$	-0.002	0.004	[-0.008, 0.005]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	-0.026	0.002	[-0.03, -0.023]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	-0.001	0.003	[-0.006, 0.003]
Asia			
$\gamma_{\log(real\ gdp\ per\ capita)}$	0.089	0.009	[0.074, 0.105]
$\gamma_{log\ (real\ gdp\ per\ capita)^2}$	0.023	0.007	[0.012, 0.034]
$\gamma_{log\ (real\ gdp\ per\ capita),t-1}$	-0.006	0.005	[-0.014, 0.003]
Scale			
$\sigma^{r}_{\gamma_{Y\to H}}$	0.036	0.008	[0.025, 0.051]