The long-run impact of artificial intelligence on global trade and economic growth *

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Abstract

This paper studies the macroeconomic impacts of artificial intelligence (AI) using a quantitative trade model with multiple sectors, multiple factors of production, and intermediate linkages. The reallocation of tasks from labour to AI services will generate productivity gains in the model, and AI will reduce operational trade costs. We build four scenarios that differ in how far less-prepared economies catch up. The simulations yield three main findings. First, AI adoption is projected to substantially boost global trade flows and economic growth: in the most favourable scenario, the diffusion of AI raises global GDP by an additional 13.2% over the next 15 years compared to the baseline. Global trade volumes are projected to be 35% larger than without AI. Second, low- and middle-income economies can capture more of these gains if they improve their digital infrastructure and ensure adequate AI deployment across the economy. Third, AI is projected to change the within-country income distribution. While all factors gain in real terms, returns shift toward capital and the skill premium declines. The magnitude of these distributional effects depends on the long-run growth rate of AI and the degree of complementarity between production factors.

Keywords: Artificial Intelligence, Computational general equilibrium, Productivity, Technology adoption, Trade Cost

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1 Introduction

Recent rapid advances in artificial intelligence (AI) are expected to bring substantial changes to the global economy. As a general-purpose technology, AI can perform complex, non-routine tasks previously requiring human labour, often at lower cost. Its effects, therefore, extend beyond individual sectors, with significant implications for costs, prices, and specialisation. These impacts will not be confined to any one economy; they will diffuse globally and reshape international trade patterns. By changing who performs which tasks and where, AI is likely to alter the composition of international goods and services trade. Building on digital trends that have already transformed global value chains and enabled remotely delivered services, AI can further reduce operational trade costs—for example, through smarter logistics and compliance—and expand the role of data and software in cross-border exchange.

However, the diffusion of AI and its benefits will depend on an economy's digital infrastructure, access to data, workforce skills, and regulatory approaches. Despite optimism about AI's potential to boost global productivity and living standards, there are also concerns about distributional impacts across and within economies (European Commission 2024; Congressional Budget Office 2024; McKinsey & Company 2024; The Economist 2025). In the long run, the key question is whether—and how—rapid AI progress translates into broader gains in productivity, trade volumes, and income, and how those gains are distributed within and across economies. In this light, we use a quantitative trade model and scenario analysis to study how AI's emergence and development may affect production structure, trade patterns, and the distribution of income within and across economies.

In this paper, we extend a standard quantitative trade model with a new sector, "AI services". The AI services sector develops ("trains") and operates AI models, that is, computer programs designed to perform tasks typically associated with human intelligence. The training and operation of AI uses labour, capital, electronic equipment, electricity, and ICT services. Once developed, these AI models can be deployed across the economy as an input in the production function, complementary with labour, with high-skilled workers being more complementary with AI services. Hence, in this approach, the projected increase in productivity requires an increased use of AI services, contrary to earlier quantitative analysis (WTO, 2024) in which only the productivity and trade cost effects were modelled, without considering the upstream demand effects for AI services and without explicitly exploring the shift from labour to AI services in the production process. The employed model features capital and three types of workers (high-skilled, middle-skilled, and low-skilled) and firms combine the labour supplied by workers with AI to produce corresponding AI-labour composites, which are further combined with capital and intermediate inputs.

In our model, AI influences the global economy through the following channels. First, firms have the opportunity to use AI to complete tasks that previously could only be completed by labour inputs, a process that generates productivity increases. Second, by using AI to complete tasks in the production process, the value-added from different types of labour is effectively replaced by a mix of labour and capital. This transformation can shift the income distribution significantly towards capital. Finally, AI reduces trade costs via several channels, including the improvement of logistics and contract enforcement, streamlining trade compliance, as well as diminishing language barriers and distance-related costs.

Four scenarios are explored based on projections of operational trade cost reductions, productivity increases related to the deployment of AI and increased production of AI services, as well as increased productivity in the production of AI (development) services:[1] (i) *Tech divergence*, where high-skilled workers benefit most and outcomes depend on the level of digital infrastructure; (ii) *Policy catch-up*, where medium-skilled workers experience the highest productivity gains and less prepared economies close half of the gap in the level of digital infrastructure; (iii) *Tech catch-up*, where medium-skilled workers experience the highest productivity gains, and economies close half of the gap in the level of digital infrastructure as in *policy catch-up*, and economies catch up in their productivity to the technological leader for tasks completed by AI; and (iv) *AI catch-up*, where economies with low relative productivity in AI (development) services compared to the rest of the economy close the relative productivity gap in AI services. Hence, the scenarios vary along four dimensions: (i) differences in projected productivity increases of different skill groups; (ii) differences in digital infrastructure impacting regions' capacity to deploy AI; (iii) the extent to which regions can catch up to the technological leader in tasks performed by AI; (iv) the extent of regions' catch-up in producing AI services. We work with scenarios in light of the profound uncertainty about the trajectory of AI and its expected impact.

The analysis generates three key findings. First, AI has strong potential to boost global trade flows and economic growth. In the most favourable scenario, where both technology and policies converge, the spread of AI is projected to add an extra 13.2% to global GDP over the next 15 years. Beyond macroeconomic growth effects, AI is expected to reshape global trade. In our projection, the spread of AI brings an additional 35% increase in global trade. This expansion is driven by three factors: (i) reduced operational trade costs as a result of the deployment of AI, with 40% to 50% of the changes in trade attributed to a reduction in trade costs across the regions; (ii) the strong growth of AI services, which have a high degree of tradability related to the concentration of production of AI services in a few regions; and (iii) the above-average productivity growth in more tradable sectors. Among broad sectors, the largest trade growth occurs in digitally-deliverable services (DDS), which include AI services, related to the fact that the largest trade cost reductions and productivity growth are expected in DDS. This also fosters trade through upstream linkages to electronic equipment and electricity.

Second, the distribution of these gains across economies hinges on AI adoption, particularly in low- and middle-income economies. Relative to *tech divergence*, *policy catch-up* featuring an improvement in digital infrastructure alone delivers an additional 3.4 percentage point increase in real GDP for low-income economies and 1.8 percentage point for middle-income economies. Including the technology level convergence in the scenario *tech catch-up* raises these additional GDP gains further to 7.7 percentage points and 3.5 percentage points, respectively. This additional gain highlights that digital infrastructure and adequate deployment in low- and middle-income economies are essential for inclusive growth in the long run. The catch-up in AI production technology, however, is shown to be less critical for income convergence across

[1] In the scenarios we also take into account the role of the level of digital infrastructure (measured with one of the components of the AI Readiness Index from the IMF)

economies.

Third, turning from cross-economy differences to income differences within economies, AI is projected to significantly alter the division of value added between capital and labour, and across skill groups. Three main trends emerge. The real rental rate on capital is projected to rise sharply by around 18%, reflecting both the substitution of labour by AI services produced with capital and labour and the relatively capital-intensive nature of AI production. Across skill groups, the real income of low-skilled workers is projected to increase the most, by 6% to 7%, while medium and high-skilled workers gain only about half as much. This reduces the global wage premium, as AI substitutes more strongly for tasks performed by high skilled workers. Regional differences also matter: in the divergence scenario, the rise in the capital rental rate is largest in high-income economies and smallest in low-income economies, whereas under the catch-up scenarios, increases are more evenly spread. For wages, catch-up plays a particularly important role for low- and middle-income economies. For example, in *tech divergence*, middle-skilled workers in low-income economies see only a 1% wage gain, compared with 8% under technology catch-up.

We conduct a battery of robustness checks on the assumptions to construct the baseline data (on the capital intensity of AI services), on the assumed growth rate of AI services, and on the key behavioural parameters in the model. For reasonable parameter values the results are robust to these changes. However, two findings are remarkable. First, if there is a large variation in the substitution elasticity between labour and AI services across skill types the skill premium can rise instead of fall as in the benchmark. This occurs only if the substitution elasticity for low-skilled workers is much larger than that for high-skilled workers—differences that appear unrealistic. Nevertheless, this result shows that the degree of complementarity does play a role in the simulations for the impact of AI on the skill premium. Second, a larger growth of AI services leads to a small reduction in the projected GDP growth. The reason is that, in our setting, a larger growth in AI services with identical productivity growth implies that the shift towards AI services generates less macroeconomic gains. Third, trade growth would rise substantially (exceeding 50%) with a larger assumed growth in AI services, which can be explained by the high tradability of AI services. This implies that a wider expansion of AI services would raise trade growth.

This paper contributes to the emerging literature on the macroeconomic outcomes of AI development and deployment (Acemoglu 2025; Korinek and Suh 2024; Cerutti et al. 2025; Erdil et al. 2025) and, more broadly, on automation (Acemoglu and Restrepo 2017; Acemoglu and Restrepo 2018a; Acemoglu and Restrepo 2022; Restrepo 2024; Acemoglu and Restrepo 2018c; Acemoglu and Restrepo 2018b; Acemoglu and Restrepo 2020b; Acemoglu and Restrepo 2020a), with a particular focus on its impacts on global trade, economic growth, and the distribution of income across countries and income groups. Acemoglu and Restrepo (2018a) discuss the potential adverse distributional effects of AI as a form of automation capable of replacing tasks previously performed by labour. Meanwhile, Acemoglu (2025) estimates modest medium-run effects of AI on TFP and GDP within a closed economy framework, and discusses its implications for distribution across income groups and between capital and labour. Aghion and Bunel (2024) offers a more optimistic view by arguing that, in addition to the task replacement, AI can boost growth through idea generation. Filippucci, Gal, and Schief (2024) estimate the TFP gains by combining evidence on the exposure of activities to AI and likely future adoption rates, and then feed the estimated TFP gains into a multi-sector general equilibrium model with input-output linkages to aggregate the output effects.

Cerutti et al. (2025) also estimate the TFP impacts of AI across broad economic sectors based on sectoral exposure to AI, preparedness, and access to AI in different economies. They then introduce these shocks into a multi-region, three-sector dynamic general equilibrium model. Their findings show that AI may exacerbate cross-country income inequality effects by disproportionately benefiting advanced economies, similar to the findings in Filippucci, Gal, Jona-Lasinio, et al. (2024). Using a different approach, Rockall, Mendes Tavares, and Pizzinelli (2025) examine the effects of AI in a closed general-equilibrium model of heterogeneous households with a task-based production function à la Moll, Rachel, and Restrepo (2022), calibrated to UK data. They find that AI adoption reduces wage inequality by displacing high-income workers but increases wealth inequality through higher capital returns. In particular, their model predicts that the wage Gini decreases by 1.7 to 3.9 percentage points, while the wealth Gini rises by 7.2 to 13.5 percentage points, accompanied by an increase in the capital income share of 5.5 to 10.2 percentage points.[2]

Finally, this paper contributes to the literature on the trade-enhancing effects of AI. For instance, Jakubik, Rotunno, and Saini (2025) study the effect of AI on international trade, combining a model of AI-driven productivity shocks with an empirical analysis of recent data, and find that higher AI exposure is strongly associated with higher exports, with heterogeneous effects across economy groups.

This paper contributes to the existing literature in four ways. First, we project the impact of AI development and deployment on global trade volumes, alongside impacts on economic growth and income distribution. We do this using a quantitative trade model featuring heterogeneous labour endowment, and input-output linkages. This setting allows us to examine the impacts of AI, including its impacts on trade and upstream sectors, in a more micro-founded manner. Second, our setting with heterogeneous labour endowments allows us to quantify the employment effects of AI differ across worker groups.[3] Third, to the best of our knowledge, we are the first to examine the trade cost-reducing impacts of AI and to quantify their impacts within a general equilibrium framework. Finally, our scenarios allow us to examine how policy and technological catch-up can influence AI deployment across the world and study their impacts. In doing so, we highlight that better-designed policies can help economies accommodate AI in a way that mitigates the cross-country inequality it may otherwise generate.

The paper is organised as follows: Section 2 contains a formal exposition of the structure of the employed model, the data employed and the calibration of behavioural parameters. Section 3 outlines the four scenarios and the calibration of the shocks included in the four scenarios. Section 4 presents the simulation results. Section 5 concludes.

[2]Rockall, Mendes Tavares, and Pizzinelli (2025) primarily report changes in wage and wealth Gini coefficients as well as capital income shares, so our results are not directly comparable with theirs.

[3]Cerutti et al. (2025) examine the cross-country income effects of AI, while Rockall, Mendes Tavares, and Pizzinelli (2025) analyse its distributional impacts in a closed-economy setting.

2 Methodology: economic model and employed data

This section describes the quantitative trade model used to conduct the simulations and the calibration of the model, describing the employed data and the behavioural parameters. We employ a recursive dynamic computable general equilibrium model with multiple sectors, multiple production factors with three types of labour, and intermediate linkages. AI services are included in the model as a tradable intermediate good which can substitute for labour. The model is calibrated to the OECD Trade in Value Added (TiVA) database extended with AI services, which is split out from the sector ICT Services.

2.1 Formal description of quantitative trade model

In each region, a representative agent collects income from factor endowments and tax receipts in each period and allocates this income to savings or household expenditures. The model is a recursive dynamic model and works with a fixed savings rate, thus abstracting from intertemporal consumption decisions. Perfectly competitive firms combine intermediate inputs, both domestically produced and imported, with capital and a composite of different types of labour and AI services. The supply of capital in period $t+1$ is a function of capital in period t plus net investment in period t. Labour supply is characterised by an upward-sloping supply function. International trade is modelled with an Armington structure and the trade-balance-to-income ratio is fixed.

The next subsections describe demand, supply, international trade and the sets of equilibrium equations.

2.1.1 Demand

There are $r = 1,..,R$ regions, $c = 1,..,C$ commodities, and $e = 1,..,E$ production factors. In each region, a representative agent allocates a fixed share, s_r, of her income, y_r, to savings, $x_r^{sa} = s_r y_r$. The rest of her income, $x_r^{pr} = (1 - s_r)\, y_r$, is allocated across all commodities c according to a non-homothetic constant elasticity of substitution (CES) utility function as in Comin, Lashkari, and Mestieri (2021):[4]

$$x_r^{pr} = e_r^{pr}\left(q_r^{pr}, p_{1r}^{pr}, .., p_{Cr}^{pr}\right) = \left(\sum_c \Omega_c \left(q_r^{pr}\right)^{(1-\theta)\varepsilon_c} \left(p_{cr}^{pr}\right)^{1-\theta}\right)^{\frac{1}{1-\theta}} \quad (1)$$

q_r^{pr} is the quantity consumed, p_{cr}^{pr} is the price of consumption on commodity c and ε_c and θ are parameters determining the income and (cross) price elasticities of demand. Employing Shepherd's lemma and differentiating expenditure, x_r^{pr}, with respect to the price, p_{mr}^{pr}, gives demand for good m, q_{mr}^{pr}:

$$q_{mr}^{pr} = \Omega_{mr} \left(q_r^{pr}\right)^{(1-\theta)\varepsilon_{mr}} \left(\frac{p_{mr}^{pr}}{x_r^{pr}}\right)^{-\theta} \quad (2)$$

[4]We use the parametrization with $g(U) = U$ which is employed in the applications by these authors: "A simple example that ensures all these conditions are satisfied is given by the
choice of $g(U) = U$ (..) , which we use in
the calibration exercise in Section 7" (Comin, Lashkari, and Mestieri (2021), page 15).

2.1.2 Supply

Perfectly competitive firms produce gross output of commodity c, q^{go}_{rc}, by combining intermediate inputs, q^{int}_{rc}, with a combination of (conventional) capital and a composite of labour of different skill levels and AI services, q^{va}_{rc}, employing a CES production function:

$$q^{go}_{rc} = \left(\left(\varpi^{va}_{rc}\right)^{\frac{1}{\upsilon}} \left(q^{va}_{rc}\right)^{\frac{\upsilon-1}{\upsilon}} + \left(\varpi^{int}_{rc}\right)^{\frac{1}{\upsilon}} \left(q^{int}_{rc}\right)^{\frac{\upsilon-1}{\upsilon}} \right)^{\frac{\upsilon}{\upsilon-1}} \tag{3}$$

There is no scope for substitution between intermediate inputs, implying a Leontief specification for intermediates purchased by sector c from sector d, q^{ii}_{rdc}:

$$q^{int}_{rc} = \min\left\{\nu_{r1c}q^{ii}_{r1c}, \ldots, \nu_{rCc}q^{ii}_{rCc}\right\} \tag{4}$$

The demand for value-added and intermediate inputs by sector c is therefore given by:

$$q^{va}_{rc} = \varpi^{va}_{rc} \left(\frac{p^{va}_{rc}}{p^{go}_{rc}}\right)^{-\upsilon} q^{go}_{rc} \tag{5}$$

$$q^{ii}_{rdc} = \nu_{rdc}\varpi^{int}_{rc} \left(\frac{p^{int}_{rc}}{p^{go}_{rc}}\right)^{-\upsilon} q^{go}_{rc} \tag{6}$$

The price index of gross output, p^{go}_{rc}, can thus be written as a function of the prices of intermediate inputs, p^{ii}_{rdc}, and the price of value added, p^{va}_{rc} as follows:

$$p^{ib}_{rc} = \left(\varpi^{va}_{rc} \left(p^{va}_{rc}\right)^{1-\upsilon} + \varpi^{int}_{rc} \left(\sum_{d=1}^{C} \nu_{rdc} p^{ii}_{rdc} \right)^{1-\nu} \right)^{\frac{1}{1-\nu}} \tag{7}$$

Value-added, q^{va}_{rc}, is a combination of capital k_{rc} and composites of labour of three skill types s (high-skilled, medium-skilled, and low-skilled) with AI services, q_{rcs}:

$$q^{va}_{rc} = a^{va}_{rc} \left(\left(\alpha^{k}_{rc}\right)^{\kappa} \left(q^{k}_{rc}\right)^{\frac{\kappa-1}{\kappa}} + \sum_{s=\{LS,MS,HS\}} \left(\alpha^{lai}_{rcs}\right)^{\kappa} \left(q^{lai}_{rcs}\right)^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}} \tag{8}$$

α^{k}_{rc} and α^{lai}_{rcs} are CES demand shifters for capital and labour-AI-services composites of labour type s respectively. Hence, the demand for capital and labour-AI-services composites and the price level of value added can be written as follows:

$$q^{k}_{rc} = \alpha^{k}_{rc} \left(\frac{p^{k}_{rc}}{p^{va}_{rc}}\right)^{-\kappa} q^{va}_{rc} \tag{9}$$

$$q^{lai}_{rcs} = \alpha^{lai}_{rcs} \left(\frac{p^{lai}_{rcs}}{p^{va}_{rc}}\right)^{-\kappa} q^{va}_{rc} \tag{10}$$

$$p^{va}_{rc} = \left(\alpha^{k}_{rc} \left(p^{k}_{rc}\right)^{1-\kappa} + \sum_{s=\{LS,MS,HS\}} \alpha^{lai}_{rcs} \left(p^{lai}_{rcs}\right)^{1-\kappa} \right)^{\frac{1}{1-\kappa}} \tag{11}$$

To produce labour-AI composites q^{lai}_{rcs}, the completion of a continuum of tasks, T_{rcs}, is required:

$$q_{rcs}^{lai} = \left(\int_{0}^{1} \left(b_{rcs} T_{rcs}(i) \right)^{\frac{\sigma_s - 1}{\sigma_s}} di \right)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{12}$$

These tasks can be completed either with labour, q_{rcs}^{l}, of skill type $s = \{LS, MS, HS\}$ or AI services combined with skill type s, q_{rcs}^{ai}.[5] β_{rcs} is the fraction of tasks completed with AI services and hence $1 - \beta_{rcs}$ the fraction completed with labour. This gives the following CES production function (see Zeira or Aghion et al., 2017):

$$\begin{aligned} q_{rcs}^{lai} &= \left(\beta_{rcs} \left(\frac{b_{rcs} q_{rcs}^{ai}}{\beta_{rcs}} \right)^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \beta_{rcs}) \left(\frac{b_{rcs} q_{rcs}^{l}}{1 - \beta_{rcs}} \right)^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \\ &= \left(\left(a_{rcs}^{ai} q_{rcs}^{ai} \right)^{\frac{\sigma_s - 1}{\sigma_s}} + \left(a_{rcs}^{l} q_{rcs}^{l} \right)^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \end{aligned} \tag{13}$$

With:

$$a_{rcs}^{ai} = \beta_{rcs}^{\frac{1}{\sigma_s - 1}} b_{rcs}; a_{rcs}^{l} = (1 - \beta_{rcs})^{\frac{1}{\sigma_s - 1}} b_{rcs} \tag{14}$$

a_{rcs}^{ai} and a_{rcs}^{l} are productivity changes driven by a reallocation of tasks, whereas b_{rcs} is an autonomous productivity change. As equation (13) shows, a_{rcs}^{ai} and a_{rcs}^{l} can be written as a function of β_{rcs}.

Hence, the demand for labour of skill type s and AI services combined with labour of skill type s can be expressed as follows:

$$q_{rcs}^{l} = \left(a_{rcs}^{l} \right)^{\sigma_s - 1} \left(\frac{p_{rcs}^{l}}{p_{rcs}^{lai}} \right)^{-\sigma_s} q_{rcs}^{lai} \tag{15}$$

$$q_{rcs}^{ai} = \left(a_{rcs}^{ai} \right)^{\sigma_s - 1} \left(\frac{p_{rcs}^{ai}}{p_{rcs}^{lai}} \right)^{-\sigma_s} q_{rc}^{lai} \tag{16}$$

$$p_{rcs}^{lai} = \left(\left(\frac{p_{rcs}^{ai}}{a_{rcs}^{ai}} \right)^{1 - \sigma_s} + \left(\frac{p_{rcs}^{l}}{a_{rcs}^{l}} \right)^{1 - \sigma_s} \right)^{\frac{1}{1 - \sigma_s}} \tag{17}$$

q_{rcs}^{ai} is a homogeneous intermediate sourced both domestically and from imports (with shares calibrated as discussed below). Hence, we can write:

$$\sum_{s = \{LS, MS, HS\}} \sum_{c} q_{rcs}^{ai} = q_{r}^{ai} \tag{18}$$

q_{r}^{ai} is the quantity of AI services demanded in region r, which is either sourced domestically or imported, as specified below.

The allocation of labour across commodities c is imperfectly mobile according to a constant elasticity of transformation (CET) function. Hence, the supply of labour in sector c rises with the return to labour in sector c, p_{rcs}^{l}, relative to the average return to labour, w_{rs}^{l}, with the

[5] b_{crs} is a productivity shifter generic across all tasks.

responsiveness governed by the elasticity of transformation, μ_l:

$$q^l_{rcs} = \left(\frac{p^l_{rcs}}{\vartheta_{rcs} w_{rc}}\right)^{\mu_s} lab_{rc} \tag{19}$$

$$w_{rs} = \left(\sum_{c=1}^{C} (\vartheta_{rcs})^{-\mu_s} \left(p^l_{rcs}\right)^{\mu_s+1}\right)^{\frac{1}{\mu_s+1}} \tag{20}$$

The supply of three types of labour is determined by an upward-sloping labour supply curve. The supply of labour is governed by an isoelastic supply function with ξ_s the elasticity of supply of skill type s:

$$l_{rs} = w_{rs}^{\frac{1}{\xi_s}} \tag{21}$$

Capital is mobile within regions. Thus, returns to capital, p^l_{rc}, are equalised across sectors and equal to r_r:

$$p^k_{rc} = r_r \tag{22}$$

$$k_r = \sum_{c=1}^{C} q^k_{rc} \tag{23}$$

The capital stock in period $t+1$, k_r, evolves according to:

$$k_{r,t+1} = (1-\delta)k_{r,t} + q^{in}_{r,t} \tag{24}$$

where δ is the depreciation rate, and $q^{in}_{r,t}$ is aggregate investment in period t. Aggregate investment is a Leontief composite of investment goods in different sectors:

$$q^{in}_r = \min\left\{\varpi^{in}_{r1} q^{in}_{r1}, \ldots, \varpi^{in}_{rC} q^{in}_{iC}\right\} \tag{25}$$

This implies the following expressions for sectoral investment demand and the price index of aggregate investment:

$$q^{in}_{rc} = \varpi^{in}_{rc} q^{in}_r \tag{26}$$

$$p^{in}_r = \sum_{c=1}^{C} \varpi^{in}_{rc} p^{in}_{rc} \tag{27}$$

2.1.3 International trade

Agents $ag \in \{pr, in, ai, fi\}$ (households, investors, firms purchasing ai intermediates and firms purchasing other intermediate inputs) divide demand, q^{ag}_{rc}, between domestic and foreign goods, $q^{so,ag}_{rc}$; $so = d, m$, according to the following CES demand function reflecting Armington preferences. Furthermore, this demand function incorporates the diffusion of ideas through trade following the approach in Buera and Oberfield (2020) and Goes and Bekkers (2023):[6]

$$q_{rc}^{so,ag} = \sum_{ag} \lambda_{rc}^{\rho_c - 1} \left(\frac{p_{rc}^{so}}{p_{rc}^{ag}} \right)^{-\rho_c} q_{rc}^{ag} \tag{28}$$

λ_{rc} denotes productivity driven by diffusion of ideas in region r in sector c. The change in productivity is an intermediate input weighted average of the level of productivity in sector-region combinations from which intermediates are sourced:

$$\Delta \lambda_{rc,t} = \alpha_t \sum_{d} \eta_{rdc,t-1} \sum_{u} (\pi_{urdc,t-1})^{1-\zeta} (\lambda_{ru,t-1})^{\zeta} \tag{29}$$

With $\eta_{rdc,t-1}$ the share of intermediate inputs sourced by sector c from sector d in region r and $\pi_{urdc,t-1}$ the share of imports sourced by sector c in region r from sector d in region u. α_t is autonomous productivity growth which is identical across regions and sectors.

Imports and domestic demand can be summed across agents, ag, to give total importer and domestic demand, q_{rc}^{so} with so the source, $so = d, m$:

$$q_{rc}^{so} = \sum_{ag} q_{rc}^{so,ag} = \sum_{ag} \left(\frac{p_{rc}^{so}}{p_{rc}^{ag}} \right)^{-\rho_c} q_{rc}^{ag} \tag{30}$$

$$p_{rc}^{ag} = \left(\left(p_{rc}^{d} + p_{rc}^{m} \right)^{1-\rho_c} \right)^{\frac{1}{1-\rho_c}} \tag{31}$$

p_{rc}^{ag} and p_{rc}^{so} are respectively the prices corresponding with q_{rc}^{ag} and q_{rc}^{so}. Since total domestic and import quantities, q_{rc}^{so}, are homogeneous across the different agents, they do not have a superscript ag.[7] The price of the domestic good, p_{rc}^{d}, is equal to the production tax, tp_{rc}, times the price of gross output defined in the previous subsection, p_{rc}^{go}:

$$p_{rc}^{d} = tp_{rc} p_{rc}^{go} \tag{32}$$

Bilateral imports from a specific partner s are determined by a CES function of aggregate

[6]The original modelling of ideas diffusion is embedded in a model of Bertrand competition as in Bernard et al. (2003), with the change in the location parameter of the Frechet distribution of productivity being a function of the location parameter of productivity in trading partners and this specification based on the diffusion of ideas through the sales of intermediates. Following Bekkers et al. (2024), we employ the same specification embedded in a model with Armington preferences which in reduced form is identical to an Eaton-Kortum model.

[7]The modelling of international trade with aggregate group-specific domestic and import demand, but group generic import demand from different sources is chosen, because group-specific aggregate import and domestic spending shares are typically available in national account data, whereas in international trade data group-specific import shares per trading partner are absent. So the data provide, for example, information on specific import and domestic spending shares of the government, private households, and each of the sectors demanding intermediates, but not on import shares from different trading partners. So called MRIO databases employ the BEC classification to generate group-specific bilateral import shares. However, with this approach it is not possible to generate group-specific bilateral import shares for each of the sectors purchasing intermediate inputs. Only a split between consumption goods, capital goods, and intermediates is feasible.

import demand, q_{rc}^{m} reflecting Armington preferences:[8]

$$q_{urc} = \tau_{urc}^{1-\rho_c} \left(\frac{tp_{uc} p_{uc}^{go}}{p_{rc}^{m}} \right)^{-\rho_c} q_{rc}^{m} \tag{33}$$

$$p_{rc}^{m} = \left(\sum_{u=1}^{R} \left(\tau_{urc} tp_{uc} p_{uc}^{go} \right)^{1-\rho_c} \right)^{\frac{1}{1-\rho_c}} \tag{34}$$

2.1.4 Equilibrium

Goods market clearing requires that total production equals the quantity of input bundles, q_{rc}^{ib}, in sector c in region r which is equal to the quantity demanded, consisting of domestic demand and import demand:

$$q_{rc}^{go} = \sum_{ag} q_{rc}^{d,ag} + \sum_{c=1}^{C} \tau_{rsc} q_{rsc} \tag{35}$$

Regional household income is the sum of factor earnings by labour and capital, net of capital depreciation plus indirect tax revenues, tr_r^{ind}:

$$y_r = \sum_{s} w_{rs} l_{rs} + k_r r_r \left(1 - \delta\right) + tr_r^{ind} \tag{36}$$

Gross investment expenditure is equal to domestic savings plus the value of depreciation minus the trade surplus:

$$p_r^{in} q_r^{in} = q_r^{sa} p_r^{sa} - \delta k_r r_r - \left(\sum_{u=1}^{R} \sum_{c=1}^{C} q_{ruc} tp_{uc} p_{uc}^{go} - q_{urc} tp_{rc} p_{rc}^{go} \right) \tag{37}$$

Furthermore, in equilibrium, the sum of trade balances is equal to zero and henceforth, the global value of savings is equal to the global value of net investments:[9]

$$\sum_{r=1}^{R} x_r^{sa} = \sum_{r=1}^{R} p_r^{in} q_r^{in} - \delta k_r r_r \tag{38}$$

Finally, we impose that the trade balance-to-income ratio is fixed in $R-1$ regions:[10]

$$\Delta \frac{\sum_{u=1} \sum_{c=1} q_{ruc} tp_{rc} p_{rc}^{go} - q_{urc} tp_{uc} p_{uc}^{go}}{y_r} = 0 \tag{39}$$

Therefore, equations (37) and (39) pin down the quantity of investment in regions r, q_r^{in}, except for the residual region for which investment is determined by equations (37)-(38).

[8] We allow for intra-regional trade. Such trade has to be considered because some regions are aggregates of different economies.

[9] In the model (38) is the omitted equation by Walras' law.

[10] Equation (38) determines the trade balance in the residual regions, thus imposing that the global value of savings is equal to the global value of investment.

2.2 Calibration of the model

We start with a description of the employed data to calibrate the baseline in 2019, including a discussion of the extension of the TiVA database with AI services. Then we turn to a discussion of the baseline calibration, followed by an outline of the construction of the baseline until 2040.

2.2.1 Data to calibrate the baseline

The model is solved by hat differentiating the equilibrium system of equations. Hence, to calibrate the model we need baseline spending shares, which are based on the Trade in Value Added (TiVA) Data Base (OECD 2023) which covers 76 economies across 45 economic activities over the period 1995-2020. We use the TiVA database to construct the majority of key data flows required. These include:

- Investment: the sum of expenditure on investment commodities, both domestic and imported, by an activity.
- Private (and government) consumption: the sum of expenditure on commodities for private household consumption. Government purchases are subsumed into the household component in the model, so government expenditure is also included in our model. The total consumption is split between domestic purchases and those that are imported.
- Intermediate inputs: expenditure on intermediate inputs by production activity (sector). The total intermediate inputs is split between domestic purchases and those that are imported.
- International trade: bilateral trade by commodity. Sum of imported intermediates and imports for final demand.
- Factor payments: value added by activity in a region.

The TiVA database was developed to provide new insights to policymakers on the value added by each economy in the production of goods and services that are consumed worldwide (OECD, 2023).[11] We further expand the insights provided by the TiVA data by applying it in a general equilibrium setting.

Factor payments by activity are split between capital (rent payments) and labour (wages). We use the latest GTAP database with 2017 as the reference year (Aguiar et al., 2023) to apportion factor payments between capital and labour for each region and activity. We calibrate a region's capital stock so that investment as a proportion of the capital stock is equal to 5.6 percent. We follow this approach to ensure that the model runs smoothly, as actual capital stock data, for example data from the IMF Investment and Capital Stock database (ICSD), presents challenges to the simulation. We use an investment to capital stock ratio of 5.6 percent as this is the global average rate from the latest GTAP database (Aguiar et al., 2023). We assume the depreciation rate in each region to be 4 percent and savings, S, is calculated as: $S = I + X - M$, where I is net investment i.e. gross investment minus depreciation, X is the

[11] TiVA indicators are derived from OECD Inter-Country Input-Output (ICIO) tables. These are constructed using statistics compiled from national, regional and international sources.

total value of exports and M is the total value of imports. Population data comes from the World Development Indicators (World Bank, 2024).

We aggregate the TiVA database to 15 sectors and 21 regions and employ data for the year 2019 to avoid distorted data because of the impact of COVID-19 on the global economy. Government expenditures are merged with private household demand into total household demand. The savings rate is obtained as a residual from the trade imbalances in TiVA and the level of investment. To make sure that the model can be calibrated some negative data points for gross investments (net investment plus changes in inventories) were eliminated by raising investment and reducing private household demand.

We then extend the database with an additional sector, "AI services". To do so, we split the TiVA sector "ICT services" into AI services and "Other ICT services." The sector AI services is defined as the sector that develops (or "trains") and operates AI models, that is, computer programs designed to perform tasks typically associated with human intelligence. Once developed, these AI models can be deployed across various sectors of the economy to perform tasks traditionally carried out by humans.

We employ the utility SplitCom, which is an RAS procedure ensuring that the database remains balanced.[12] This utility requires inputs of sales shares, cost shares, and trade shares of the subsector split out and with these inputs adjusts the resulting input-output and trade matrices iteratively, while ensuring that the sum of sales and absorption of the newly created sectors is identical to the values of the old split up sector. We describe in turn the assumptions on cost shares, the size of the AI services sector, sales shares, and trade shares.

We start by specifying the cost structure of AI services. According to Cottier et al. (2025), the training and operation of AI rely on the following inputs: labour, capital, semiconductors and other server components (classified under electronic equipment (COM) in TiVA), electricity, and ICT services such as data storage and internet transmission. They report that the cost shares of electronic equipment (chips, servers, etc.), electricity, and labour are approximately 70:5:25. This estimate indicates that the intermediate share of AI is higher than the broader ICT sector, driven by its high demand for inputs from upstream sectors. Building on these broad assumptions, we further assume that the capital–labour ratio in the AI sector is 50% higher than in the ICT sector, reflecting the greater role of intangible capital in AI services. In addition, we assume that the AI sector allocates 5% of its total expenditures to itself and 45% to the broader ICT sector, capturing the reliance of AI training on pre-existing models and ICT infrastructure such as data centres. Finally, we assume that high-skill labour accounts for 60% of total labour costs, while middle- and low-skill labour each account for 20%, consistent with the higher skill intensity of AI development compared with the broader ICT sector.

Next, we estimate the size of the AI services sector with two alternative approaches. First, UN Trade and Development (2025) estimate the AI sector to be $256 billion. Second, based on the assumed cost structure of AI services, we back out the global scale of AI-related expenditures. Employing the cost structure of AI development discussed above, chips account for 19% of total development costs. Nvidia, the major supplier of AI chips, reported $47.4 billion in revenue

[12]The RAS acronym derives from "Row and Column Scaling, which is a matrix balancing algorithm extensively used in economic and statistical data processing.

from AI and data centre chips in 2024. Assuming that Nvidia is the player with a majority market share, this implies that global AI-related expenditures are approximately $249 billion, which aligns with the estimate reported by UN Trade and Development (2025).[13]

To determine the sales shares across sectors, we allocate the household and investment shares of AI sales in line with those in the broader ICT sector. The sales of AI services as intermediates to other sectors are determined based on the sales shares of the sector ICT services multiplied by the AI exposure index in each region and sector, which is described in detail below in the calibration of productivity shocks.

The final step is to determine the regional distribution of AI trade flows. We begin by determining global production shares of AI based on each region's share in global AI patents as a proxy for technological capacity and thus production of AI services. To that end, we use the Worldwide Patent Statistical Database (henceforth PATSTAT), a collection of bibliographic patent data from more than a hundred patent offices produced by the European Patent Office. We define AI patents using the taxonomy proposed by WIPO (2019), which we update by including new CPC classes containing AI-related terms following Trefler and Sun (2022). Economies' shares of AI patents are then calculated based on the priority application country for each AI patent filed in the years 2010-2022.[14]

Next, the expenditure shares of each region in global spending on AI services is based on the share of spending on ICT services. Holding both production and expenditure shares fixed, we then estimate the AI cross-country trade share matrix by minimising its deviation from the observed trade matrix of ICT services, subject to the constraint that no single economy cannot source more than 95% of its AI services from one single foreign economy. In this way, our imputation yields production and expenditure patterns consistent with the assumption described above, while ensuring that the trade structure mirrors the trade structure of ICT services as closely as possible, thereby incorporating real-world trade factors to the highest possible extent.

Like the broader ICT sector, AI production is highly concentrated. The top three producers, the United States, China, and Western Europe, account for 59% of global ICT output and an even larger 62% of AI output. On the demand side, these three regions together represent 58% of global AI demand, compared with 59% for ICT. However, AI is considerably more trade-intensive: 37% of global AI demand is met through imports, compared with only 14% for ICT. However, for net importers of AI services the import share can be as high as 78%.

[13]To obtain 2019 values, a 14% annual growth rate in reverse is applied. However, this step is inconsequential since this growth is applied to obtain 2024 data in the baseline construction described below. We determine the size of the AI services sector based on production costs rather than sales for two reasons: (i) reliable sales data are limited, and (ii) many AI firms are currently operating at a loss.

[14]The use of the office of priority filing as a proxy for patent origin is motivated by many missing values reporting the residence of patent inventors and applicants directly. According to Thomas and Murdick (2020), the country of priority application accurately captures the first inventor country for AI-related patents in over 80 per cent of cases. We downsized the implied Chinese production share of AI by 37.5% to account for the differences in the patent filing system across economies and better match the observed ICT trade shares in our RAS procedure.

2.2.2 Calibration of parameters

The parameter governing the substitution elasticity of household consumption across sectors, θ, is equal to 0.1, following Comin, Lashkari, and Mestieri (2021). The parameters determining the income elasticity across sectors, ε_{cr}, vary across sectors, with higher elasticities for services sectors and smaller elasticities for agriculture.

The elasticity of substitution between intermediate inputs and value added, υ, is equal to 0.9 based on the structural estimates of Atalay (2017). The choice between intermediates is Leontief implying an elasticity of substitution of 0, also based on the structural estimates reported in Atalay (2017). The substitution elasticity between capital and labour-AI-services composites is equal to 0.9. This value is selected to ensure that the substitution elasticity between capital and different labour-AI composites is not deviating from the average substitution elasticity between labour and AI services.

The substitution elasticity between AI services and labour, σ_{sk}, varies by skill type based on variation in measures of complementarity between labour and AI.

To obtain a measure for the degree of complementarity, we follow the logic of Auer, Kopfer, and Sveda (2025), who distinguish between AI exposure of an occupation's core and supplementary (i.e., nonessential) elements. Intuitively, if an occupation's core elements can be automated, it is considered substitutable. On the other hand, if an occupation's supplementary tasks can be automated, it is considered complementary to AI. Hence, whether a job is considered substitutable or complementary depends not so much on the distribution of AI incidence across occupation's components, but on the centrality of the exposed components to the occupation in question. Whether a job component is core or not to an occupation is determined using its respective importance scores reported in O*NET. Adopting the approach of Auer, Kopfer, and Sveda (2025) to the AI occupational exposure (AIOE) score for each occupation, we construct the contribution of core and supplementary abilities to the overall exposure index:

$$\text{AI exposure score}_{o,}^{type} = \frac{\sum_{j \in \text{type}} A_j w_{jo}}{\sum_j w_{jo}}, type = \{core, supplementary\}$$

Type varies across the ability-occupation dimension. We repeat this step for both AI exposure scores, considering highly and moderately advanced AI. To obtain skill-level measures of potential complementarity with AI, we aggregate the share of supplementary abilities' contribution to the total exposure index across high-, middle- and low-skilled workers. The obtained values for the measure of complementarity is multiplied by 1.5 to obtain values for substitution elasticities in the model, leading to substitution elasticities varying between 0.7 and 1.1 as there is no straightforward way to convert the complementarity measures from task data into substitution elasticities employed in the economic model. In robustness checks, we vary the conversion employing both proportionally smaller substitution elasticities compared to the benchmark and employing substitution elasticities varying more than proportionally across skill types compared to the complementary measures.

The Armington substitution elasticities, ρ_c, are based on structurally estimated values with TiVA data reported in Rubinova and Sebti (2021). The elasticity of transformation determining the degree of mobility of labour across sectors, μ_s, is equal to 5 for all skill types. This implies labour is nearly perfectly mobile across sectors, and the differential returns across sectors are thus limited. The labour supply elasticity is equal to 0.5 like in Bekkers, Francois, and Rojas-Romagosa (2018) based on estimates in the macro-literature (Chetty 2012). Finally, the parameter governing the strength of diffusion of ideas, ζ, is equal to 0.48. This is based on a calibration in Bekkers, Humphreys, et al. (2025) targeting GDP growth rates with the model as close as possible to those between 1995 and 2020. The autonomous productivity growth is equal to global population growth, $\alpha_t = 1.00$. Table 1 and 2 provide an overview of the parameters in the model.

Table 1: Selected model parameters

Parameter	Description	Value	Source
Preferences and Demand			
θ	Household demand elasticity	0.10	Comin, Lashkari, and Mestieri (2021)
ε_c	Income elasticity of sectoral consumption		Comin, Lashkari, and Mestieri (2021)
Production and Technology			
ν	Substitution between value added and intermediates	0.90	Atalay (2017)
κ	Substitution between capital and labour–AI composite	0.90	Calibrated
σ_s	Substitution across tasks		Own calculation based on Felten, Raj, and Seamans 2021
σ_{LS}	- low-skilled	1.16	
σ_{MS}	- middle-skilled	0.94	
σ_{HS}	- high-skilled	0.78	
Labour Supply			
μ_s	Cross-sector labour supply elasticity	5	Bekkers and Francois (2018)
ξ_s	Aggregate labour supply elasticity	0.50	Chetty (2012)
Trade Parameters			
ρ_c	Armington trade elasticity		Rubinova and Sebti (2021)
Growth and Diffusion			
α	Autonomous productivity growth	1.00	Bekkers et al. (forthcoming)
ζ	Diffusion strength of ideas	0.48	Bekkers et al. (forthcoming)
δ	Capital depreciation rate	0.04	GTAP calibration

Notes: The values presented in "Substitution across tasks" section are used in the Policy catch-up, Tech catch-up and AI catch-up scenarios. In the Tech divergence scenario, the values used are $\sigma_{LS} = 1.15$, $\sigma_{MS} = 0.89$ and $\sigma_{HS} = 0.52$.

Table 2: Sector-specific elasticities

Sector	ε_c	ρ_c	Sector	ε_c	ρ_c	Sector	ε_c	ρ_c	Sector	ε_c	ρ_c
AGC	0.32	4.86	COM	2.17	4.9612	ELE	2.17	4.9612	ELY	2.17	4.9612
AI	1.6187	4.73	ICT_Res	1.6187	4.73	MEQ	1.00	4.85	MET	1.00	4.61
MIN	0.41	5.06	MXT	0.41	5.06	OBS	1.6187	4.64	OTG	1.00	4.65
OTS	1.6187	4.73	PCH	1.00	4.65	TRA	1.62	4.25	TRP	1.62	4.36
UTC	1.4911	4.18									

3 Scenario description and calibration

Because of the high degree of uncertainty about the future trajectory of AI, we work with different scenarios. This section first motivates and introduces four scenarios, which vary in the degree of policy and technological catch-up of regions, and then describes in detail how the scenarios are calibrated.

3.1 Description of the four scenarios

To analyse the impact of AI on the global economy, we incorporate (operational) trade cost reductions as well as a rising demand for AI services leading to AI-deployment related productivity increases. We develop four scenarios in light of the profound uncertainty about the trajectory of AI and its expected impact. The scenarios vary along four dimensions: (i) differences in projected productivity increases of different skill groups; (ii) differences in digital infrastructure impacting regions' capacity to deploy AI; (iii) the extent to which regions can catch up to the technological leader in tasks performed by AI; (iv) the extent of regions' catch-up in producing AI services. Comparing these scenarios allows us to explore a range of possible outcomes for global trade and production patterns as AI becomes more widespread:

- **Tech divergence.** In this scenario, referred to as *technology divergence within and between economies*, high-skilled labour experiences the highest productivity gains from AI deployment, related to the introduction of more advanced AI technologies. Furthermore, actual policies related to digital infrastructure affect the ability of economies to exploit productivity and operational trade cost improvements associated with the deployment of AI, and there is no catch-up in the level of digital infrastructure.

- **Policy catch-up**. In this scenario, referred to as *policy catch-up between economies and technology synergies within economies*, medium-skilled workers experience the highest productivity gains, related to the introduction of more basic types of AI similar to those currently deployed. Furthermore, economies with smaller scores of digital infrastructure readiness partially catch up to better performing regions (closing 50% of the gap in scores of digital policies).

- **Tech catch-up.** In this scenario, referred to as *technological and policy catch-up between economies*, the productivity of medium-skilled workers improves most, and economies converge in terms of digital infrastructure readiness (identical to *policy catch-up*). On top of that, the productivity in tasks performed with AI converges to the productivity of the best-performing region in these tasks.

- **AI catch-up.** This scenario, referred to as *AI technological catch-up*, is identical to *policy catch-up* and adds on top of that, economies with low productivity in producing AI services (in the data with low production shares) partially catch up (closing 100% of the inferred relative productivity gap in AI services relative to economy-level productivity) and thus will also be able to produce more AI services. This scenario makes it possible to analyse the importance of being strong in the production of the strongly growing sector

AI services. However, the scenario only considers convergence within economies between AI services and other sectors and not between economies, because there is no reason for catch-up in the production of AI services to technological leaders.

3.2 Calibration of the four scenarios

Next, we describe how the shocks related to the growth of AI are calibrated, starting with a description of the calibration of operational trade cost reductions, followed by the calibration of the AI-deployment related productivity improvements, the productivity increases related to technological catch-up and the productivity increases related to AI technological catch-up.

3.2.1 Calibration of Trade Cost Shocks

AI is projected to reduce operational trade costs through six channels: (i) compliance costs, (ii) language barriers in terms of translation, (iii) language barriers in terms of informal communication (iv) logistics costs in terms of timeliness of shipments, (v) the improvement of contract enforcement, and (vi) the decrease in distance-related trade costs. To determine the size of the trade cost reductions, we combine gravity estimation of the impact of proxies of the six channels on trade flows. More formally, we regress inferred trade costs (based on international relative to intra-national trade) on proxies for the six channels (controlling for other determinants of trade costs). We combine the regression results with insights from case studies on the impact of AI on trade costs and the results of the ICC-WTO joint business survey to gauge the size of the change in the proxies for the six channels.

The first channel is a reduction in compliance costs, as it will become less costly to comply with regulations (LOG_DOC_EXP). The compliance cost measure employed is the World Bank's Doing Business indicator "Documentary compliance to export", defined as the hours needed to comply with all documentary requirements to export. This generates ad valorem equivalent (AVE) trade costs for documentary compliance. In counterfactual scenarios, we assume that the documentary compliance scores fall by 30%. This value is based on the results of the ICC-WTO joint business survey of AI potential (ICC-WTO 2025).[15]

The second channel is the improvement in contract enforcement processes with AI solutions for document management in courts ($CONTRACT$). Many commercial courts face backlogs of cases that lead to delays in proceedings, which negatively affect the business environment in general. There are AI solutions that aim to improve this situation and substantially accelerate document management in courts. For instance, IBM recently introduced "an AI assistant named OLGA that offered case categorisation, extracted metadata", and could "bring cases to faster resolution". This may reduce the processing time of cases by half according to (IBM 2025). To measure the potential impact of AI solutions that overcome case backlog in commercial courts on trade costs, we include the Doing Business indicator "Contract enforcement: trial and judgment time" in the trade cost regression. This indicator reports the number of days between the moment the case is served and the expiration of the appeal time limit. In the counterfactual scenarios, we assume that AI solutions will accelerate the timeline of commercial

[15] We use employment-weighted averages of the scores reported in the survey.

disputes by 5 percent. We use a more conservative approach (5% instead of 50%) as a substantial share of trial time does not depend on the promptness of document processing.

The next two channels are related to the potential impact of AI on language-related trade barriers. AI could reduce such barriers in two ways, i.e., by facilitating the translation of both written and spoken communication, and by reducing searching and matching costs. To proxy for these two language-related barriers, we use indicators of "common official language" (COL) and "common spoken language" (CSL), respectively, developed by Melitz and Toubal (2014). The former captures the potential of using machine learning for translation purposes, while the latter captures the influence of common language on trade (and trade costs) through, for example, the ease of communicating informally and building trust in networks. In the counterfactual scenarios, we assume that translation-related costs, captured by COL, decrease by 25.5% - based on firm-size-weighted results of the ICC-WTO joint business survey of the AI potential (ICC-WTO 2025). At the same time, to model the decrease in searching and matching costs we use a conservative approach and assume convergence toward the mean value of CSL for lagging economy pairs.

The fifth channel is the improvement in logistics planning and costs ($TMLNS$). The range of ways in which AI may affect logistics costs is broad. However, we focus on the "timeliness" of shipments, i.e. the frequency with which shipments are delivered within the scheduled or expected delivery times. To proxy this channel, we use the timeliness component of the Logistics Performance Index, which varies from 0 to 5. To capture the potential impact of AI, we calculate the difference between the maximum possible value for this indicator (five) and the actual indicator and include it in the regression of inferred trade costs on trade cost proxies. In the counterfactual scenarios, the reduction in logistics-related trade costs is 19.5%, based on the ICC-WTO joint business survey of AI potential (ICC-WTO 2025). In other words, we assume that AI will improve the timeliness of shipments by decreasing delays by approximately one-fifth. As developing economies and LDCs tend to have a higher frequency of delays, such an improvement will have a convergence effect.

The last channel considered is the reduction in distance-related trade costs ($PDIST$). AI has the potential to improve route optimisation for shipments. By decreasing the time needed and the level of operational costs, such solutions that can reduce"economic distance" between trading partners. For instance, the recent case of an AI-powered route optimisation system developed by Hyundai for use on board domestic commercial vessels in Korea demonstrates average fuel savings of 5.3% (Kosmajac 2025). This case also suggests that route optimization saves not only fuel but also the time required to deliver the shipment, which in turn results in a decrease of costs related to crewing, coordination, and non-shipping services. Therefore, we assume that the 5.3% saving in fuel implies a 5.3% drop in total distance-related operational trade costs. We use the port distance from Bekkers, Francois, and Rojas-Romagosa (2018) to estimate distance-related trade costs. In this experiment, we do not limit ourselves to maritime transport, which dominates in international shipping. Instead, we acknowledge that AI route optimisation has potential in other modes of transport, implying that we assume that the reduction in distance-related costs is expected to occur for all modes of transport. At the same time, we do not use this indicator for the tertiary sector (services).

To determine the potential for trade cost reductions because of AI solutions, we regress inferred trade costs on a set of determinants described above, supplemented with the (importer-specific) WB-WTO Services Trade Restrictiveness Index [16] ($STRI$) and several gravity variables from Conte, Cotterlaz, and Mayer (2022), such as the existence of an FTA and colonial linkages. Inferred trade costs are calculated based on the approach originally proposed by Head and Ries (2001) as well as Chen and Novy (2011) and applied by Novy (2013), among others. Hence, iceberg trade costs between the economy r and u in sector c, τ_{ruc}, can be expressed as the ratio of international relative to intra-national trade flows in trade models with CES-preferences such as the Armington model used in the simulations:

$$\tau_{ruc} = \left(\frac{X_{ruc} X_{urc}}{X_{rrs} X_{uuc}} \right)^{\frac{1}{2(\rho_c - 1)}} \tag{40}$$

X_{ruc} is the value of sales from economy r to u in sector c and ρ_c the substitution elasticity between goods of different origin in sector c. We refer to this measure of trade costs as the Head and Ries (HR) Index. It is calculated based on GTAP Data for 2017.

We regress the HR Index in equation (40) on the variables described earlier for three aggregate sectors: primary (agriculture and mining), secondary (manufacturing), and tertiary (services) [17] The estimation results are in Table 3.

$$\begin{aligned} \ln \tau_{ij} = {} & aTFPha + \beta_l \ln LOG\_DOC\_EXPi + \beta_e \ln CONTRACT_{ij} + \beta_t \ln COLij + \beta_c \ln CSLij \\ & + \beta_b TMLNSj + \beta_b PDISTij + X'\theta + \epsilon_{ij} \end{aligned} \tag{41}$$

In our scenarios, trade cost shocks vary based on an economy's ability to grasp the potential of AI solutions. To do that, we use a bilateral preparedness index (ranging from 0 to 1) calculated based on two pillars of the AI preparedness index (Cazzaniga et al. 2024), Human capital and Digital Infrastructure. We limit ourselves to using only two pillars of the AI preparedness index since the other two pillars are already captured by variables included in the gravity model. In scenario 1 we assume that there is no catch-up and the AVE trade cost reductions are proportionally scaled down by the preparedness index. In scenarios 2-4 lagging economies catch up in terms of their AI preparedness index by half to the economy-pairs with the highest scores of AI preparedness index.

Figure 1 displays the projected cumulative trade cost reduction in *tech divergence* (with full scaling down for lagging economies) and *policy catch-up* (with catch-up by half in the bilateral AI preparedness index) over the period 2021 to 2040. The figure shows that LDCs are projected to benefit from the largest trade cost reductions. This is because these regions have the greatest potential to leverage AI to lower compliance costs, logistics costs, and costs related to language barriers. In terms of channels, the largest projected trade cost reduction is expected from decreased logistics and compliance costs.

[16] We adjust WB-WTO values for intra-EEA pairs using the ratio of OECD intra-EEA STRI related to OECD STRI.

[17] We estimate for the three broad sectors, because we do not have sufficient information at the detailed sectoral level.

Table 3: Trade Costs Analysis Results

	(1) Primary sector	(2) Secondary sector	(3) Tertiary sector
FTA	-0.0153***	-0.0213***	-0.00241***
	(0.000170)	(6.62e-05)	(0.000243)
CLNY	-0.0401***	0.00225***	0.00692***
	(0.000524)	(0.000173)	(0.000569)
LANDLOCKED	0.114***	0.0594***	0.0633***
	(0.000268)	(7.96e-05)	(0.000270)
CONTIG	-0.0981***	-0.152***	-0.126***
	(0.000212)	(7.68e-05)	(0.000302)
CREDIT	-0.0131***	-0.181***	-0.123***
	(0.000230)	(0.000144)	(0.000414)
CSL	-0.00847***	-0.0115***	-0.387***
	(0.000402)	(0.000142)	(0.000402)
COL	-0.00925***	-0.0177***	-0.143***
	(0.000265)	(0.000101)	(0.000275)
PDIST	0.0671***	0.0656***	0.0875***
	(8.34e-05)	(2.97e-05)	(0.000114)
CONTRACT	0.0255***	0.121***	0.242***
	(0.000182)	(7.58e-05)	(0.000272)
LOG_DOC_EXP	0.0160***	0.0363***	0.0647***
	(4.54e-05)	(2.14e-05)	(7.82e-05)
TMLNS	-0.251***	-0.549***	
	(0.000524)	(0.000257)	
STRI			0.148***
			(0.000215)
Constant	0.158***	0.494***	-0.174***
	(0.00158)	(0.000692)	(0.00228)
Observations	4,161,483	28,978,997	9,488,281
R-squared	0.497	0.624	0.615

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2 displays the projected cumulative trade cost reduction under the same two scenarios across different sectors. It is clear that the services sectors are expected to incur the highest cumulative trade cost reduction despite the fact that services trade is affected only through four of the six channels. As expected, the weakening of language-related barriers has the highest potential for services trade. At the same time, we can see that compliance costs play an important role for secondary and tertiary sectors, while timeliness is crucial for primary and secondary sectors.

Figure 1: Cumulative Trade Cost AVEs (%) Averaged by the Importer over 2020-2040

Source: own calculation
Notes: the figure depicts the relative sizes of the cumulative AVE trade cost reductions in the observation period at the regional level. The percentage changes are not additive.

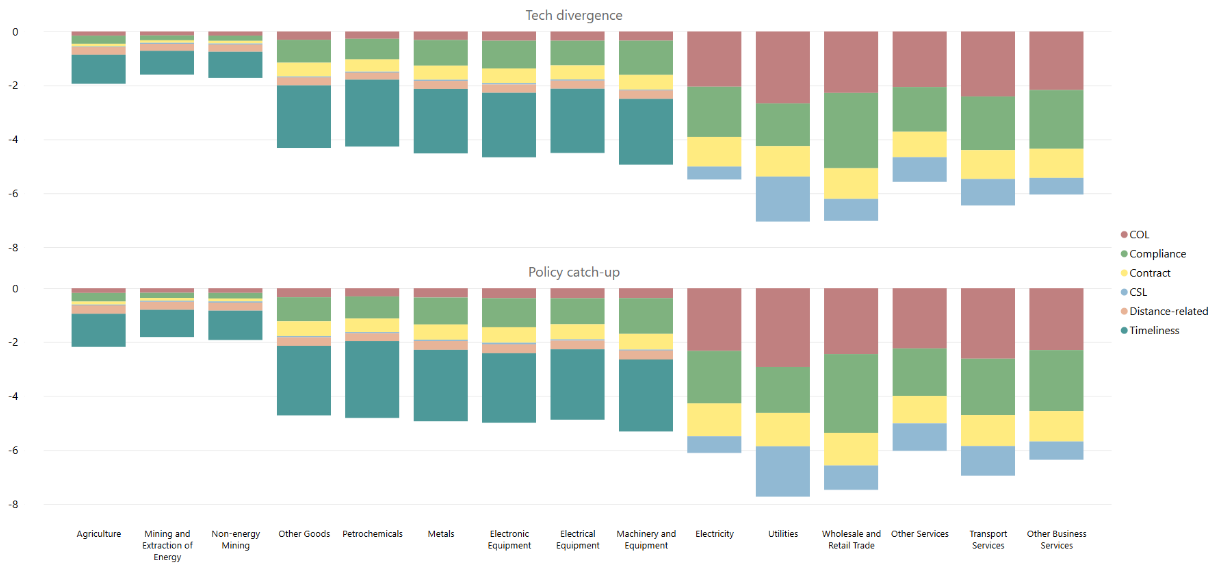


Figure 2: Cumulative Trade Cost AVEs (%) Averaged by the Sector over 2020-2040

Source: own calculations
Notes: the figure depicts the relative sizes of the cumulative AVE trade cost reductions in the observing period at the sectoral level. The percentage changes are not additive.

3.2.2 Calibration of AI-deployment related productivity increases

Productivity rises in the model because of a reallocation of tasks from labour to AI and because of autonomous productivity increases related to productivity catch-up, which are discussed further below. To calibrate this reallocation and the associated productivity increase, we employ projections on both the growth in the AI services sector and on the expected productivity increases. To see how this works in the model, we start by writing relative changes in conventional productivity, a^L_{sk} and a^{AK}_{sk}, as a function of changes in the share of tasks completed with AI, β_{sk}, using equation (14):

$$\widehat{a^{ai}_{rcs}} = \frac{1}{\sigma_s - 1}\widehat{\beta_{rcs}} + \widehat{b_{rcs}} \tag{42}$$

$$\widehat{a^{l}_{rcs}} = -\frac{1}{\sigma_s - 1}\frac{\beta_{rcs}}{1-\beta_{rcs}}\widehat{\beta_{rcs}} + \widehat{b_{rcs}} \tag{43}$$

The autonomous productivity increases are omitted in the remainder. The level of the share of tasks conducted with AI, β_{rcs}, and its change, $\widehat{\beta_{rcs}}$, are unobserved. Hence, we employ external projections on total productivity growth and the growth in the AI services sector to calibrate β_{rcs} and $\widehat{\beta_{rcs}}$ and thus $\widehat{a^{ai}_{rcs}}$ and $\widehat{a^{l}_{rcs}}$. To do so, we define the relative change in the productivity of the labour-AI-services composite, $\widehat{LP_{rcs}}$ as a value share weighted average of the productivity shifters $\widehat{a^{ai}_{rcs}}$ and $\widehat{a^{l}_{rcs}}$ with as weight the value (cost) share of AI, γ_{rcs}:

$$\widehat{LP_{rcs}} \equiv (1-\gamma_{rcs})\,\widehat{a^{l}_{rcs}} + \gamma_{rcs}\widehat{a^{ai}_{rcs}} \tag{44}$$

Substituting equation (44) into equations (42)-(43) thus gives:

$$\widehat{LP_{rcs}} = \frac{1}{\sigma_s - 1}\left(\frac{\gamma_{rcs}-\beta_{rcs}}{1-\beta_{rcs}}\right)\widehat{\beta_{rcs}} \tag{45}$$

Equation (45) shows that if the share of tasks conducted with AI, β_{rcs}, is equal to the value share of AI services, γ_{rcs}, the productivity growth is zero.

Inverting and substituting back into equations (42)-(43) gives:

$$\widehat{a^{ai}_{rcs}} = \frac{1-\beta_{rcs}}{\gamma_{rcs}-\beta_{rcs}}\widehat{LP_{rcs}} \tag{46}$$

$$\widehat{a^{l}_{rcs}} = -\frac{\beta_{rcs}}{\gamma_{rcs}-\beta_{rcs}}\widehat{LP_{rcs}} \tag{47}$$

Next, the change in the cost share γ_{rcs} on AI capital can be written as a function of the change in the task share on AI capital, β_{rcs}, as follows (derivations in Appendix A):

$$\widehat{\beta_{rcs}} = \frac{1-\beta_{rcs}}{1-\gamma_{rcs}}\widehat{\gamma_{rcs}} \tag{48}$$

The level of the (unobserved) share of tasks conducted with AI, β_{rcs}, can now be solved as a function of $\widehat{LP_{rcs}}$, $\widehat{\gamma_{rcs}}$ and β_{rcs} by combining equations (45) and (48):

$$\beta_{rcs} = \gamma_{rcs} + (1-\sigma_{rcs})\,\frac{\widehat{LP_{rcs}}}{\widehat{\gamma_{rcs}}} \tag{49}$$

Finally, writing the relative change in the AI capital cost share, $\widehat{\gamma_{rcs}}$, as a function of the relative change in sales of AI capital, $\widehat{p^{ai}_{rcs}q^{ai}_{rcs}}$, gives:

$$\widehat{\gamma_{rcs}} = (1-\gamma_{rcs})\,\widehat{p^{ai}_{rcs}q^{ai}_{rcs}} \tag{50}$$

Substituting equations (48)-(50) into equations (46)-(47) gives for the productivity changes of

AK and L:

$$\widehat{a^{ai}_{rcs}} = \widehat{LP_{rcs}} - \frac{(1-\gamma_{rcs})^2}{(1-\sigma_s)} \widehat{p^{ai}_{rcs} q^{ai}_{rcs}} \tag{51}$$

$$\widehat{a^{l}_{rcs}} = \widehat{LP_{rcs}} + \frac{\gamma_{rcs}(1-\gamma_{rcs})}{(1-\sigma_s)} \widehat{p^{ai}_{rcs} q^{ai}_{rcs}} \tag{52}$$

Equations (51)-(52) make clear that the conventional productivity terms for AI services and labour are negatively respectively positively impacted by changes in the size of AI services if $\sigma_s < 1$. The reason is that with (gross) complementarity between labour and AI services (implying $\sigma_s < 1$) a rising share of AI services requires a positive labour productivity shock and a negative AI productivity shock (see for further discussion Aghion et al., 2017).

Hence, we need to obtain an estimate of both the projected growth in AI services and the projected productivity growth of AI deployment. Starting with the growth in AI services, we employ projections on the AI market-size growth from a Statista market report projecting 26% annual growth (Statista 2024). As a robustness check, we use UNCTAD's *Technology and Innovation Report 2025*, which projects 38% annual growth (UN Trade and Development 2025).

Projected productivity growth across the four scenarios is calculated in four steps. First, we employ projections for average productivity growth in the US based on Aghion and Bunel (2024). Second, we employ the index of AI occupation exposure (AIOE) developed by Felten, Raj, and Seamans (2021) to calculate variation in projected productivity growth by occupation. We distinguish between two types of AI: highly advanced AI with automation of all relevant abilities (Scenario 1) or moderately advanced AI with automation of all relevant abilities except for those ranked with difficulty exceeding a certain level of difficulty (Scenarios 2-4). We map the AIOE to economic sectors segmented by skill levels, using US employment data from the Bureau of Labor Statistics for 2022 with skill level groups following the broad skill level associated with the international classification of occupations. Third, we convert the sector-skill specific productivity growth projections for the US into estimates for all other economies employing ILO data on occupation shares. Fourth, we multiply the projected productivity effects with the digital infrastructure preparedness (DIP) index from the IMF AI Preparedness Index (AIPI) (Cazzaniga et al. 2024) as a proxy for an economy's ability to capture the positive impact of AI. In Scenario 1 we employ the measured DIP index, whereas in Scenarios 2-4 we assume that economies with a lower DIP index close 50% of the gap with the economies with the highest scores.

Next we provide a more detailed exposition of the four steps to derive the productivity increases imposed exogenously on the model. First, we start with the economy-wide average productivity growth for the US, employing projections from Aghion and Bunel (2024). Aghion and Bunel (2024) estimate the TFP effect of AI using the methodology by Acemoglu (2025), who in turn relies on the theoretical model from Acemoglu and Restrepo (2018d). According to this approach, the TFP impact can be derived as a function of (i) the GDP share of tasks impacted by AI and (ii) the average cost savings from AI in those tasks. Based on evidence in the academic literature, Acemoglu (2025) derives the values 0.199 for the first component and 0.27 for total value of average labour cost savings. In addition, Acemoglu (2025) introduces two additional components: (i) the profitability or cost-effectiveness of AI solutions and (ii) the labour share per industry. The first is based on the assumption that not all AI solutions will be cost-effective in the medium term. The second is needed to transform labour costs savings into overall costs savings from AI at the task level at the aggregate level. Using another layer of economic literature and US labour statistics, Acemoglu (2025) gets respective values of 0.23 and 0.57. As a result, the methodology by Acemoglu (2025) presents the productivity effect as a function of four components (i) the GDP share of tasks impacted by AI, constrained by (ii) the share of profitable AI solutions for those exposed tasks, and (iii) the average cost savings from using AI in those tasks adjusted by (iv) the labour share of AI-exposed occupations. Multiplying all four and annualising over the 10-year horizon, Acemoglu (2025) gets the yearly TFP gains of 0.07 percentage points.

Using the same methodology, Aghion and Bunel (2024) revise the magnitude of the three first components based on the more recent AI literature and propose to consider them in terms of ranges: (i) 0.185-0.68 for the GDP share of tasks impacted by AI; (ii) 0.23-0.8 for the share of profitable AI solutions for those exposed tasks; (iii) $0.27 - 0.4$ for the average cost savings from using AI in those tasks, while (iv) the labour share of AI-exposed occupations stays constant at 0.57. As a result, Aghion and Bunel (2024) state that AI may lead to an annual TFP increase in the US by the range of 0.07-1.24 percentage points over the next 10 years.

In this paper, we employ only the upper-bound projection of Aghion and Bunel (2024). However, as the CGE simulations are long-term and forward-looking, we disregard the profitability constraint of AI and we consider a 14-year horizon. This leads to an average annual TFP increase of 1.035 percentage points per year (compared to 1.015 if the profitability constrain would remain in place).

Second, we transform the economy-wide estimates of productivity gains due to AI adoption to estimates varying by sector and skill. To do that, we employ the AI occupation exposure (AIOE) developed by Felten, Raj, and Seamans (2021). To construct this index, Felten, Raj, and Seamans (2021) identify ten broad applications of AI technology based on the Electronic Frontier Foundation description. [18]

The list includes both applications pertaining to the latest breakthroughs in generative AI, but also its earlier uses such as translation and pattern recognition.[19] The ten AI applications are accompanied by a matrix of application-ability relatedness, linking each AI application to occupational abilities as defined in the O*NET data. This generates AI exposure for abilities. Exposure for occupations, measured by the AIOE, is then calculated as a weighted average of ability-specific exposure, with the weights of each ability given by the mean of the importance and difficulty scores of abilities [20] defined for each occupation-ability pair in O*NET. More formally, for each occupation the AIOE score for occupation o is calculated as follows:

[18] The Electronic Frontier Foundation is a non-profit organization dedicated to digital rights. Among its activities, it tracks and maintains data on the development of artificial intelligence across different AI applications, using verified sources such as academic papers.

[19] The full list of applications used in Felten, Raj, and Seamans (2021) includes abstract video games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modelling, translation, speech recognition, and instrumental-track recognition.

[20] The importance score measures how crucial a specific ability is for performing a job, while the difficulty score quantifies the degree of complexity or sophistication at which the ability is performed in a given occupation

$$AIOE_o = \frac{\sum_j AI_j w_{jo}}{\sum_j w_{jo}} \tag{53}$$

AI_j is the measure of an ability's j overlap with AI applications for occupation, and w_{jo} is the mean of importance and difficulty scores of ability j for occupation o. Finally, we normalize the AIOE score to take values from 0 to 1.

The described AI exposure index implies that all abilities in all occupations may be affected by the AI. However, the current stage of AI capabilities is not that high yet. Therefore, we also calculate the AIOE for moderately advanced AI. This follows the logic introduced by Auer, Kopfer, and Sveda (2025) who note that in the short-term the impact of AI is limited by the skill's level difficulty that AI technology can currently perform. We adapt their methodology and introduce a difficulty threshold sourced from O*NET, above which an ability cannot be taken over by AI even if AI overlaps with the ability in scope. Specifically, if the difficulty level of an ability is higher than 4 out of the maximum score of 6 for a given occupation, we consider it not exposed to AI.

Each occupation is therefore associated with two AIOE-based indices: one representing highly advanced AI (automation of all relevant abilities, as in the AIOE index) and one representing moderately advanced AI (automation of all relevant abilities except for those ranked with difficulty exceeding 4). The AIOE for moderately advanced AI is employed in Scenarios 2-4, whereas the AIOE for advanced AI is employed in Scenario 1.

Third, we calculate sector-skill specific AI exposure scores, using US employment across occupations as weights based on data from the Bureau of Labor Statistics for 2022 for the US and ILOSTAT data on employment by occupation and sector for all other 160 GTAP regions. Skill types are defined based on the broad skill level associated with the international classification of occupations.[21] To calculate sector-skill exposure scores for all 160 GTAP regions, we employ economy-specific employment data by occupation level and sector from ILOSTAT as weights:[22]

$$AIOE_{rcs} = \frac{\sum\limits_{o} emp_{rcso} AIOE_o}{\sum\limits_{o} emp_{rcso}} \tag{54}$$

With $AIOE_o$ defined in equation (53) and emp_{rcso} the number of people employed in sector c in region r of skill type s in occupation o sourced from the ILOSTAT. In consequence, productivity shocks vary by skill type s, sector c, and region r and are calculated for two AI capability levels (advanced or moderate). We combine the $AIOE_{rcs}$ scores in equation (54) with average total factor productivity (TFP) growth to calculate the projected TFP growth varying by region r, sector c, and skill type s, also converting TFP growth into labour productivity growth employing labour income shares from the GTAP Data Base.

Finally, to account for additional variation in a region's ability to capture the positive impact

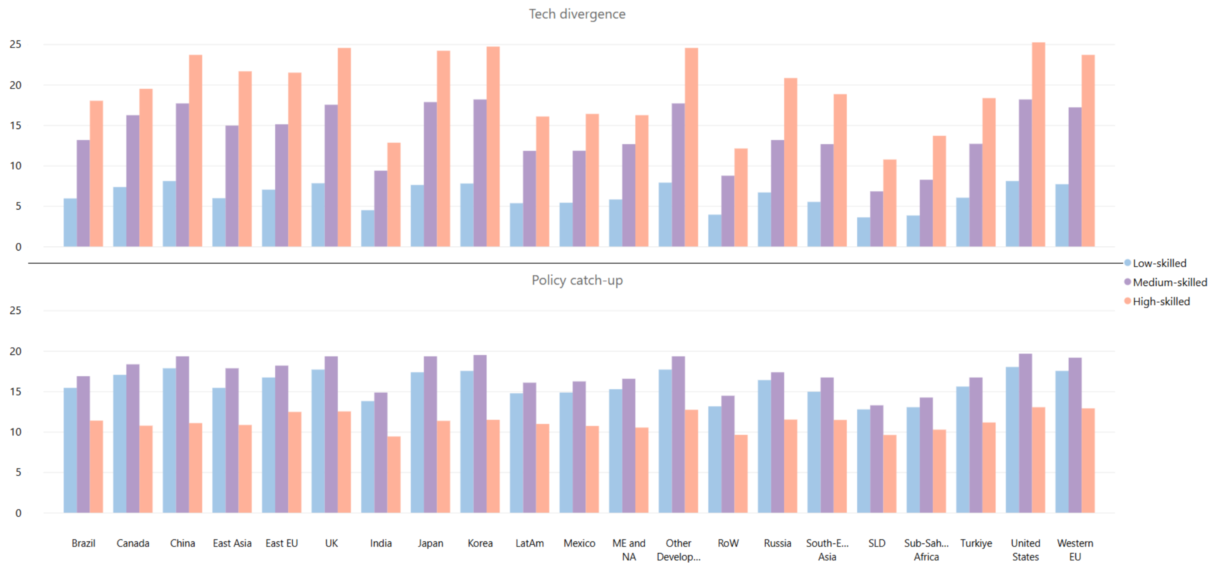
[21]The skill level of each occupation is based on skill classification for major occupational groups of the International Standard Classification of Occupations (ISCO-08), in which groups 1-3 are high-skill; 4-8 are medium-skill and 9 is low-skill. This classification is mapped to US Standard Occupational Classification (SOC2018) occupations.

[22]To compensate for the loss of information due to the use of 1-digit occupations available through the ILOSTAT, we complement the data with granular occupations from the US labor market as weights when aggregating up to 1-digit ISCO occupations.

of AI, we use the digital infrastructure preparedness (DIP) from the IMF AI Preparedness Index (AIPI) (Cazzaniga et al. 2024). We use only this part of the AIPI for two reasons. First, we believe the lack of quality of digital infrastructure is the main hindrance for an economy's ability to reap the benefits of using AI solutions. Second, the data used for productivity shocks capture, at least partially, other dimensions used in AIPI, such as human capital potential through the labour force structure used in calculations. The digital infrastructure preparedness is normalised relative to the US level and does not exceed one. In our scenarios, we employ DIP to scale down the calculated labour productivity growth proportionally. In particular, in Scenario 1 we employ the DIP, while in Scenarios 2-4 we assume that lagging economies catch-up to the highest scoring economy by half.[23]

Figure 3 displays cumulative labour productivity growth shocks for *Tech divergence* and *Policy catch-up* for the three skill types. In *Tech divergence*, assuming advanced AI, high-skilled workers experience the highest productivity growth in every region, whereas in *Policy catch-up*, assuming moderately advanced AI, productivity growth is lowest for high-skilled workers, with productivity growth similar for medium-skilled and low-skilled workers.

Figure 3: Cumulative Productivity Growth (%) by the Region and Labour-Skill Level over 2027-2040



Source: own calculation
Notes: the figure depicts the relative sizes of the cumulative productivity growth from AI deployment in the observing period at the labour-skill level.

3.3 Calibration of productivity shocks based on catch-up

In Scenario 3 *Tech catch-up*, we include an additional productivity shock on top of the AI-deployment productivity shock based on the assumption that all economies become equally productive in the completion of the tasks conducted by AI. The motivation is that each economy can do tasks completed by AI inputs with the same productivity. To operationalize this, we

[23]For example, an economy with a DIP of 0.5, will have a DIP of 0.75, given that the highest scoring economy has a DIP of 1.

proceed as follows. We define the productivity in tasks that are AI-able in the technology leader in period t as $b_{Lcs,t}^{AIA}$. If we assume that economies can catch up to the productivity level of the technological leader for the share of tasks that are AI-able, β_{rcs}, the productivity increase of region r is given by:

$$\frac{b_{rcs,t}}{b_{rcs,t-1}} - 1 = \beta_{rcs} \left(\frac{b_{Lcs,t}^{AIA}}{b_{rcs,t-1}^{AIA}} - 1 \right) - 1 \tag{55}$$

To calculate this equation, we need to obtain the share of AI-able tasks, β_{rcs}. This share is equal to the value of AI-able tasks in the structural model. We employ the final value for β_{sk} (so in 2040 after all AI-able tasks are AI-automated). At that point, β_{rcs} is equal to the cost share of tasks conducted by AI, γ_{rcs}. The final period task share is appropriate, because we assume that, for this final share, there will be convergence of productivity levels in this scenario.

For the ratio of productivities, $\frac{b_{Lcs,t}^{AIA}}{b_{rcs,t-1}^{AIA}}$, in the technological leader relative to region i, the ratio of labour productivities is operationalised through the ratio of GDP per capita values in 2023, a variable available in the data employed for the model.[24]

3.4 Calibration AI technology catch-up

Scenario 4, *AI catch-up*, assumes that productivity in producing AI services relative to productivity in other sectors converges to the productivity level of AI services relative to other sectors of the region with the highest relative productivity in AI services. As such it enables us to analyse the importance of catching up in the production of AI services, something that could also be enabled by a shift from AI development to AI adaptation. However, since productivity in AI services cannot be measured so far, we infer it with an approximation from production shares.

More specifically, productivity in region r in sector c can be approximated by the average productivity of region r, b_r, times the share region r produces in sector c relative to the share region r produces in all other sectors u:

$$b_{rc} \approx b_r \left(\frac{sh_{rc}}{\sum_u sh_{ru}} \right)^{\frac{1}{\rho_c - 1}} \tag{56}$$

We can now assume that regions catch up in terms of the relative productivity of AI relative to other sectors, giving:

$$\widehat{b_{rc}} = \left(\left(\frac{\frac{sh_{Lc}}{\sum_u sh_{Lu}}}{\frac{sh_{rc}}{\sum_u sh_{ru}}} \right)^{\frac{1}{\rho_c - 1}} - 1 \right) \tag{57}$$

Equation (57) can be calculated based on the production share of the (relative) technological leader in AI services relative to its overall production share, relative to the same ratio in region r. It is important to emphasise that this reflects only the relative convergence of the AI sector of an economy relative to other sectors and not absolute convergence of productivity of the AI

[24] This is necessarily an approximation, since average labour productivity might not align with productivity in tasks that are AI-automated.

sector.

4 Simulation Results

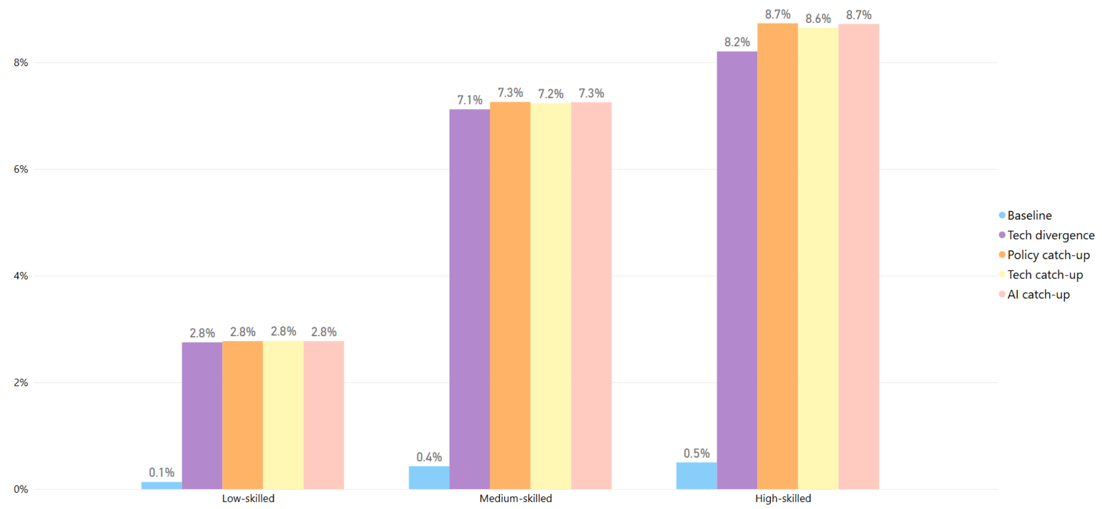
Building on the model and scenarios described in the previous section, we now turn to our main findings. We describe in turn how the reallocation of tasks from labour to AI services and the associated productivity increases as well as the reductions in trade costs are projected to change the production structure, trade flows, output, and factor returns in the long run. In the last subsection, we further describe the results of a set of robustness tests.

4.1 AI and the production structure

The analysis starts with projected shifts in the production structure. Figure 4 shows the projected worldwide share of AI services in the combination of labour and AI services by 2040 both in the baseline without AI and in the four AI scenarios. Compared with the initially small baseline, in which only between 0.1% and 0.5% of tasks are completed by AI, this share is projected to increase to around 2.8% for low-skilled workers, to around 7.2% for middle-skilled workers, and up to 8.7% for high-skilled workers. The difference between the shares in the different scenarios and the baseline share can be interpreted as the share of labour tasks shifted to AI.

The results project significant variation across skill groups, with the largest shifts from labour to AI services occurring among high-skilled and middle-skilled workers. AI is likely to be used for information processing tasks that are common in middle and high-skilled work while many low-skilled jobs involve non-routine physical and social tasks that are difficult and costly to automate.

Figure 4: Share of AI Capital in AI-Capital-Labour Composite in 2040, by Labour-Skill Level.

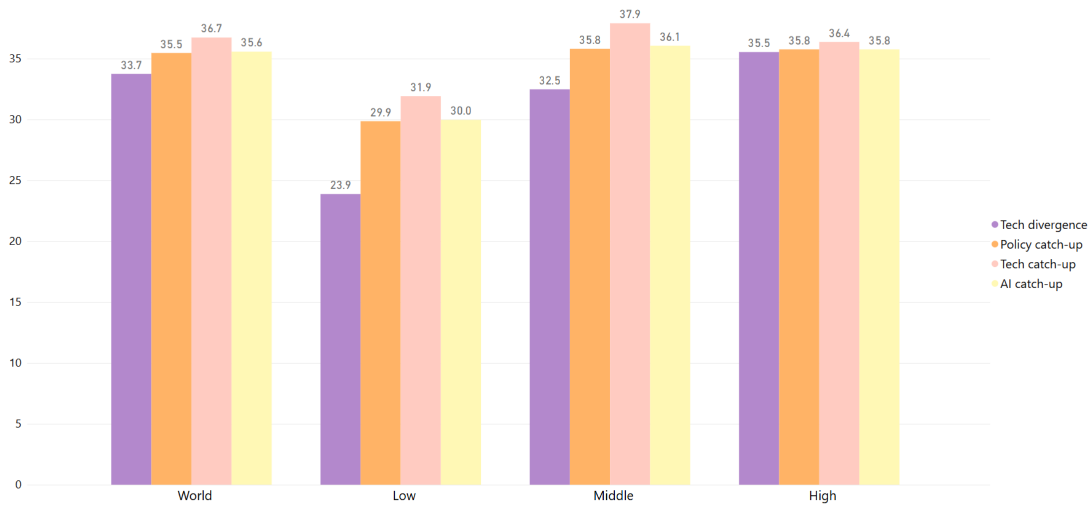


Notes: The figure displays the share of tasks which can be done with labour and AI, which are completed by AI, split by labour skill type, for four scenarios and the baseline scenario in which the growth of the AI sector is minimal.

4.2 Trade Impacts

Next we turn to the changes in trade patterns. We project a large increase in global aggregate trade, see Figure 5, with global real exports increasing by between 34% and 37% by 2040, compared to baseline, as a result of the shocks introduced across the four different scenarios. This large increase in trade is driven by three factors: (i) reduced operational trade costs as a result of the deployment of AI, with around two-fifths of the changes in trade attributed to a reduction in trade costs; (ii) the strong growth of AI services, which have a high degree of tradability related to the concentration of production in a few regions; and (iii) the above-average productivity growth in more tradable sectors.

Figure 5: Cumulative Change in Real Exports by 2040, Globally and by Income Level.

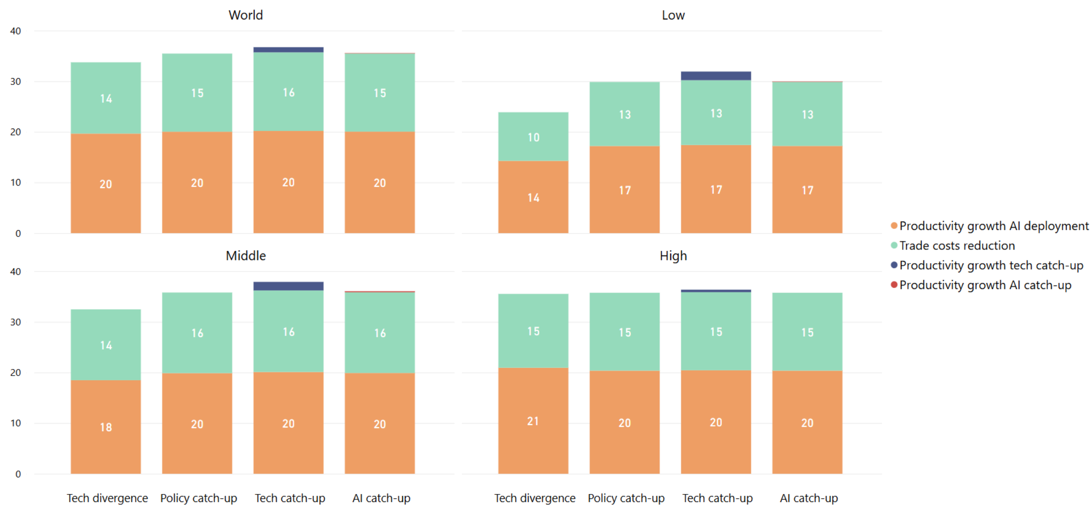


Notes: This figure displays the cumulative change in real exports over 2025-2040 for four scenarios in deviation from the baseline, both for world exports and aggregate regions split by income level.

Figure 5 demonstrates that in high-income regions, the projected changes in real exports display little variation across scenarios, with changes in real exports of around 36% by 2040, compared to baseline. The preparedness index for economy-pairs where at least one partner is a high-income economy is already close to the frontier so we see little catch-up in the high-income group. In contrast, low-income regions see much larger changes in trade in *policy catch-up* and *tech catch-up* than under *tech divergence*. *Policy catch-up* raises the change in real exports by six percentage points to 30% compared with the 24% increase under *tech divergence*, while *tech catch-up* adds a further two percentage points, raising the projected trade growth to 32%.

In Figure 6 we decompose the changes into the four shocks introduced in the model, productivity growth related to a shift in tasks from labour to AI, trade cost reductions, productivity growth related to technology catch-up, and productivity growth in the AI sector related to AI catch-up. Depending on the scenario, 50–60% of trade growth is explained by productivity gains from AI deployment, with the remainder largely attributable to projected reductions in trade costs. As expected, technology catch-up has the largest impact on low-income economies and plays virtually no role for high-income economies. Catch-up in AI productivity generates only minimal additional trade effects.

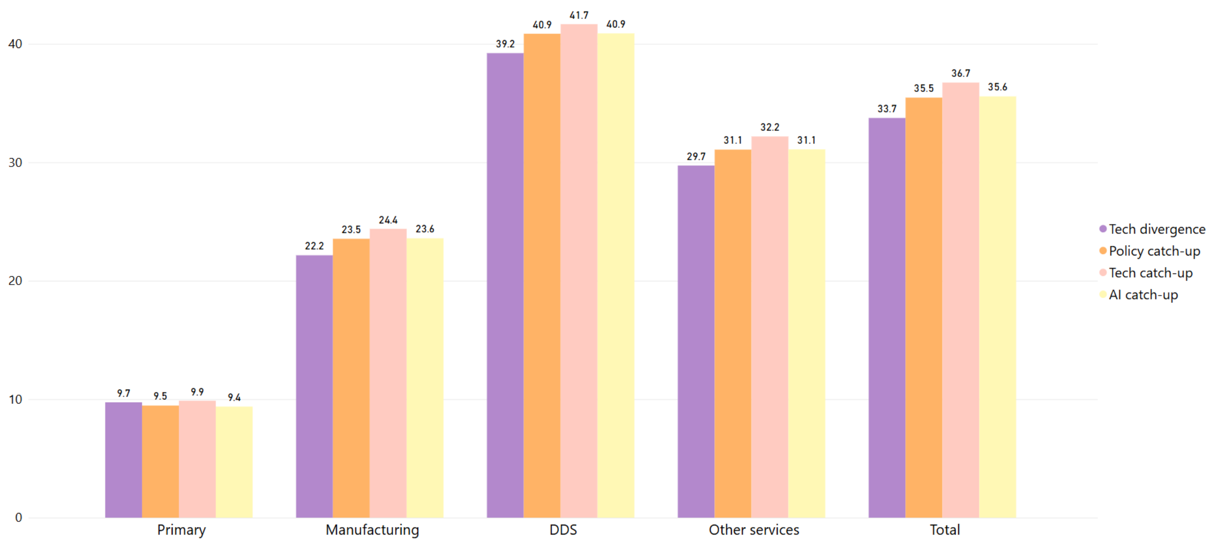
Figure 6: Cumulative Change in Real Exports by 2040, Globally and by Income Level, with Decomposition of Channels.



Notes: This figure displays the cumulative change in real exports over 2025-2040 for four scenarios in deviation from the baseline, both for world exports and aggregate regions split by income level. The changes are further decomposed into the channels of AI impact we consider.

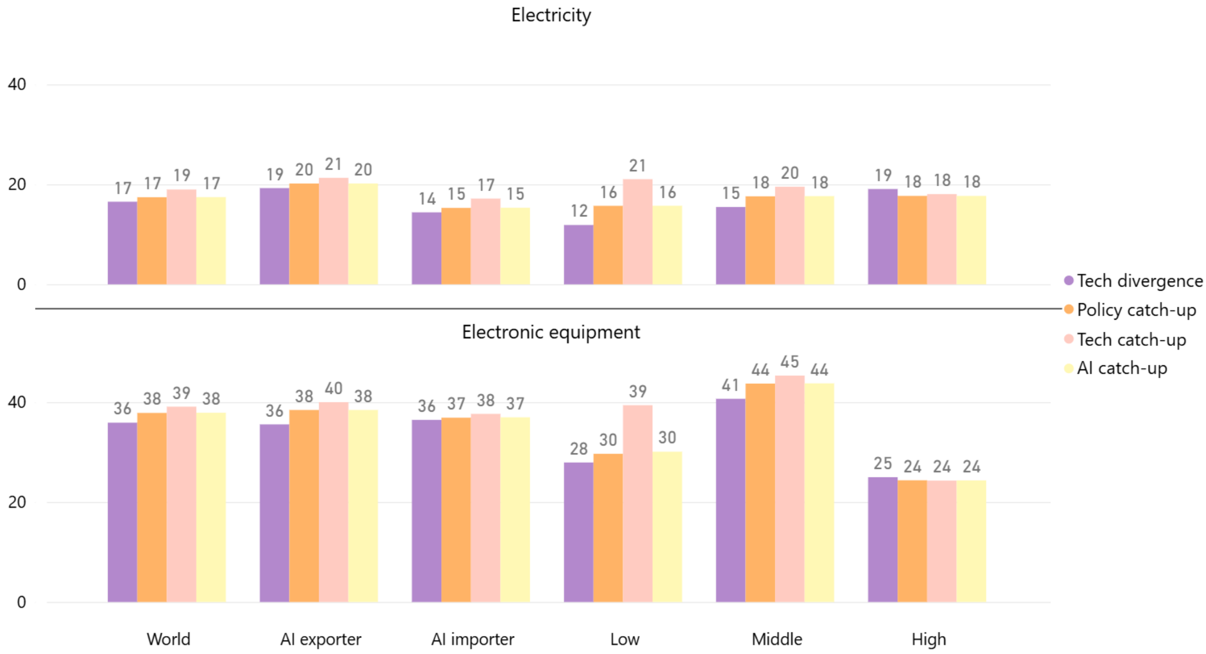
Among broad sectors (Figure 7), the largest trade growth is projected to occur in the digitally-deliverable services (DDS) sectors ($\sim 40\%$), which includes AI services, followed by other services ($\sim 30-32\%$), manufacturing ($\sim 22-24\%$), and primary sectors ($\sim 9\%$). Trade growth is highest for DDS for two reasons. First, AI services (part of DDS) are projected to expand rapidly by assumption. Second, the other DDS sectors benefit most from productivity gains of AI deployment. Third, DDS is expected to benefit most from trade cost reductions as shown above.

Figure 7: Cumulative Change in Global Real Exports by 2040 on Aggregated Sector Level



Notes: This figure displays the cumulative change in real exports over 2025-2040 for four scenarios, in deviation from the baseline, for aggregate sectors. DDS is digitally-deliverable services.

Figure 8: Cumulative Change in Output of Electricity and Electronic Equipment over 2025-2040 for Four Scenarios



Notes: The figure displays the change in the quantity of output of electricity in the upper panel and of electronic equipment in the lower panel, cumulative over 2025-2040, for four scenarios in deviation from the baseline, globally and for regions split by being an AI net exporter or AI net importer and by income level. AI net exporters and net importers are defined by calculating net exports (exports minus imports) in AI for each region.

4.3 Upstream impacts

Rising demand for AI services will also have value chain effects upstream. Figure 8 shows the projected change in the production of electronic equipment (of which semiconductors are an important component) and electricity, both globally and across aggregate regions. The expansion of AI services increases global demand for these key intermediate inputs, by 19% for electricity and by up to 39% for electronic equipment.

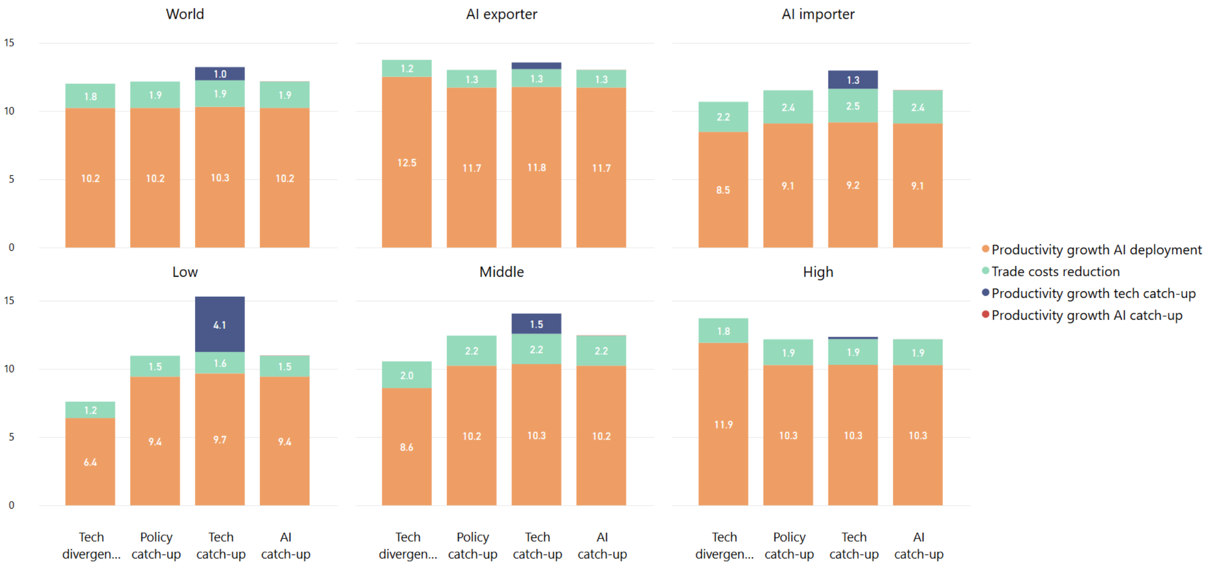
Across regions, we find that the projected increases in the production of electronic equipment are similar across both AI exporters and AI importers, with production increasing by between 36% to 40% and 36% to 38%, respectively. We also find that the projected increases in electricity production are higher in AI exporters than in AI importers, reflecting that electricity production is localised. Instead, electronic equipment is highly tradable and therefore is not necessarily produced in the AI exporting regions. In fact, Figure 8 shows that the largest projected increase in electronic equipment production is expected in middle income economies, thus reflecting the upstream international spillover effects of AI expansion.

4.4 GDP Impacts

Next, we turn to GDP effects. Figure 9 displays the projected change in real GDP, globally and for different regions across the different scenarios.

This figure generates three main insights. First, the aggregate GDP effects are substantial.

Figure 9: GDP Impacts Across Regions with Decomposition of Channels



Notes: This figure displays the cumulative change in real GDP from 2025-2040 for four scenarios in deviation from the baseline, both globally and for aggregate regions, split by income level and between AI net exporters and AI net importers. The changes are further decomposed into the channels of impact of AI deployment. AI net exporters and net importers are defined by calculating net exports (exports minus imports) in AI for each region.

The change in global real GDP ranges from 12.0% to 13.2% across scenarios. This result suggests that the potential gains from AI services advancement and deployment are substantial. Our projections are more optimistic than those reported in the existing literature. For instance, Acemoglu (2025) projects a 1.1% increase over the next 10 years, while Cerutti et al. (2025) project a relatively higher 4% expansion over the same period. By comparison, our simulations project a 7.2% increase in global real GDP over the next decade. This difference can be attributed to two main factors: (1) we adopt a more optimistic view of the productivity gains from AI, following Aghion and Bunel (2024); and (2) we account for the trade cost reduction effects of AI, which we find to generate non-trivial contributions to GDP growth.

Second, the figures show that in *tech divergence* there would be a divergence of income levels: GDP is projected to grow almost twice as much as a result of AI in high-income economies (13.7%) compared to low-income economies (7.6%). This gap narrows substantially in *Policy catch-up* with projected changes in real GDP of 11.0% and 12.2% for low-income economies and high-income economies, respectively. In this scenario, middle-income economies are projected to see larger real GDP growth (12.4%) than high-income economies. Hence, improvements in digital infrastructure, essential for the deployment of AI, play an important role in the catch-up of income levels.

In *tech catch-up*, changes in real GDP in low-income and middle-income economies are projected to be larger as a result of AI than in high-income economies, with their projected GDP increase rising to 15.3% and 14.1%, respectively. In this scenario, it is assumed that economies catch up to the productivity level of the technological leader for tasks that are AI-automated. Therefore, it is important that AI deployment generates similar productivity gains in the tasks it replaces across regions. This helps ensure that the benefits of AI are distributed more evenly

Third, *AI catch-up* has only a very limited impact on GDP and therefore does not lead to much income convergence. In this scenario, we raise in each economy the relative productivity of AI services relative to the rest of the economy to that of the frontier economy. We find that this has limited macroeconomic catch-up effects. The reason is that AI production remains too small to meaningfully affect the wider economic gains from AI expansion.

To expand on these results, we find that both policy and technological catch-up are important for income convergence between economies Technological catch-up in the scenario *tech catch-up* enables economies to converge in productivity levels to the technological leader for tasks that can be AI automated. The catch-up in AI production technology, on the other hand, is not critical for income convergence. The reason is threefold. First, AI is relatively tradable like other digitally-deliverable goods. Therefore, an economy's own AI production capacity is not necessary to benefit from AI deployment advancements. Second, the share of the AI sector is relatively small despite its rapid growth, so economy-wide productivity gains coming from AI deployment are more important than the productivity advancements within the production of AI. Third, although net exporters of AI services benefit from the shift towards AI services, this shift does not play a dominant role in the difference in projected income effects. While there is a positive correlation between the AI production share and the projected income change, this correlation is weak. Moreover, *AI catch-up* does not impact the gains for either AI-importing or AI-exporting economies significantly.

Figure 9 illustrates the GDP contributions of the four channels through which AI affects the global economy. Across all scenarios and regions, productivity gains from the direct deployment of AI play the most important role, generating roughly a 10 percentage point increase in world GDP. The contribution of reduced trade costs is also quantitatively significant, contributing about 1.8 percentage points to global GDP growth. Furthermore, technology catch-up from AI adoption in low- and middle-income economies leads to an additional 3.9 percentage point increase in GDP for low-income economies and 1.6 percentage points for middle-income economies. These results highlight that economies with lower baseline productivity have greater potential to benefit from the diffusion of AI. The GDP impacts of AI productivity catch-up are minimal.

Comparing the GDP effects in *tech divergence* with *policy catch-up* shows that the GDP gains of the high-income group falls slightly. This raises the question of whether the gains of low-income economies, because of catch-up, lead to smaller gains of the high-income group, which would imply that the gains are (partially) a zero-sum game. This is not the case. The reason for the smaller projected GDP increases for the high-income group in *policy catch-up* is that there are two changes when moving from tech divergence to policy catch-up. Low-income economies partially catch up in their level of digital infrastructure, implying larger productivity increases as AI is more readily deployed. Second, the type of AI moves from advanced AI to basic AI, implying larger productivity shocks for low-skilled and medium-skilled workers and smaller productivity shocks for high-skilled workers. Since high-income economies are, on average, more high-skilled intensive, this reduces the average productivity gains for high-income economies.

This can be shown by introducing an adjusted scenario without policy catch-up in digital infrastructure but a move from Advanced AI to Basic AI. The results are displayed in Figure A.1 in the Annex, which includes a scenario called *tech divergence basic*. The figure shows that high-income economies lose when moving from *tech divergence* to *tech divergence basic*, with the productivity shocks going from Advanced AI to Basic AI, corresponding to lower productivity gains for high-skilled workers, which are dominant in the high-income economies. Next, when moving from *tech divergence basic* to *policy catch-up* the lowest income regions such as India and SSA gain further, because they improve their digital infrastructure in policy catch-up and thus get larger productivity shocks. However, for high-income economies, their GDP gains largely remain the same, with some marginal gains from the catch-up in the low- to middle-income countries. So, there is no zero sum kind of mechanism, as expected.[25]

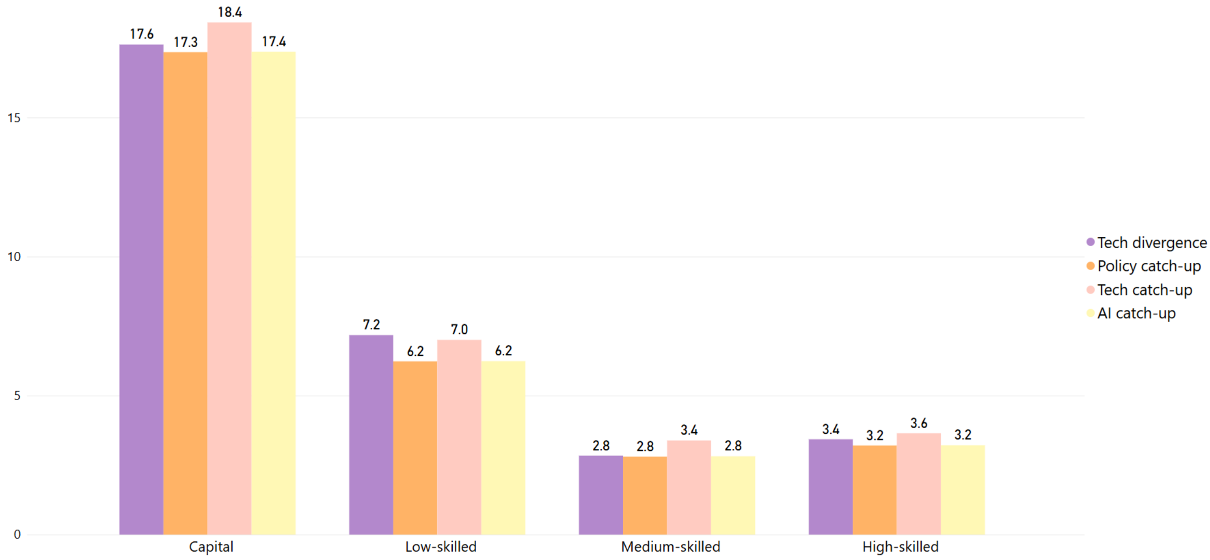
4.5 Distribution Impacts

In this subsection, we explore the impact on the functional income distribution by evaluating the projected changes in the real rental rate on capital and the real wages of high-skilled, medium-skilled, and low-skilled workers. Three main forces shape the impact of AI on the demand for production factors and thus their remuneration. On the one hand, higher productivity raises output and, in turn, increases demand for labour and capital. Second, some tasks previously performed by labour will be done by AI, which reduces the demand for labour and raises the demand for capital. Phrased differently, value added previously generated by labour is being replaced with value added generated with a combination of capital and labour, which is relatively capital-intensive. As a result, AI is expected to promote rental rates on capital and place downward pressure on employment and wages. The share of tasks for which labour is replaced by AI varies across skills, with the share replaced by AI about 3% for low-skilled workers, 7% for medium-skilled workers and 9% for high-skilled workers. Third, the impact of the reallocation of tasks on factor remuneration depends both on the projected productivity growth, which varies across scenarios and on the degree of complementarity between AI and labour and between the AI-labour composite and capital. A higher degree of complementarity of a production factor with AI services will make the impact on its factor remuneration more positive. As explained in Section 2.2.2, our model is calibrated in a way such that that the degree of complementarity is higher (and the substitution elasticity) is lower for high-skilled workers and that the substitution elasticity between the AI-labour composites and capital is equal to the average elasticity between labour and the AI composites.

In light of these forces, our simulations generate three main findings on the impact of AI on the functional income distribution. First, all production factors are projected to see their real factor remuneration increase. Figure 10 shows that the real rental rate is projected to increase by 17-18% across the different scenarios by 2040, whereas the projected increase in wages varies between about 3% for high-skilled and medium-skilled workers and 6%-7% for

[25] A zero-sum mechanism would also be curious, because larger productivity gains in low-income economies should typically benefit other economies on average. Only in very specific cases could high-income economies lose if emerging economies catch up, i.e. if the catch-up takes place in a very skewed way in their comparative advantage sectors (see for example Samuelson (2004) in a simple Ricardian model).

Figure 10: Cumulative Change in Global Real Factor Prices



Notes: The figure displays the cumulative change in global real factor prices of the production factors over 2025-2040 for four scenarios in deviation from the baseline.

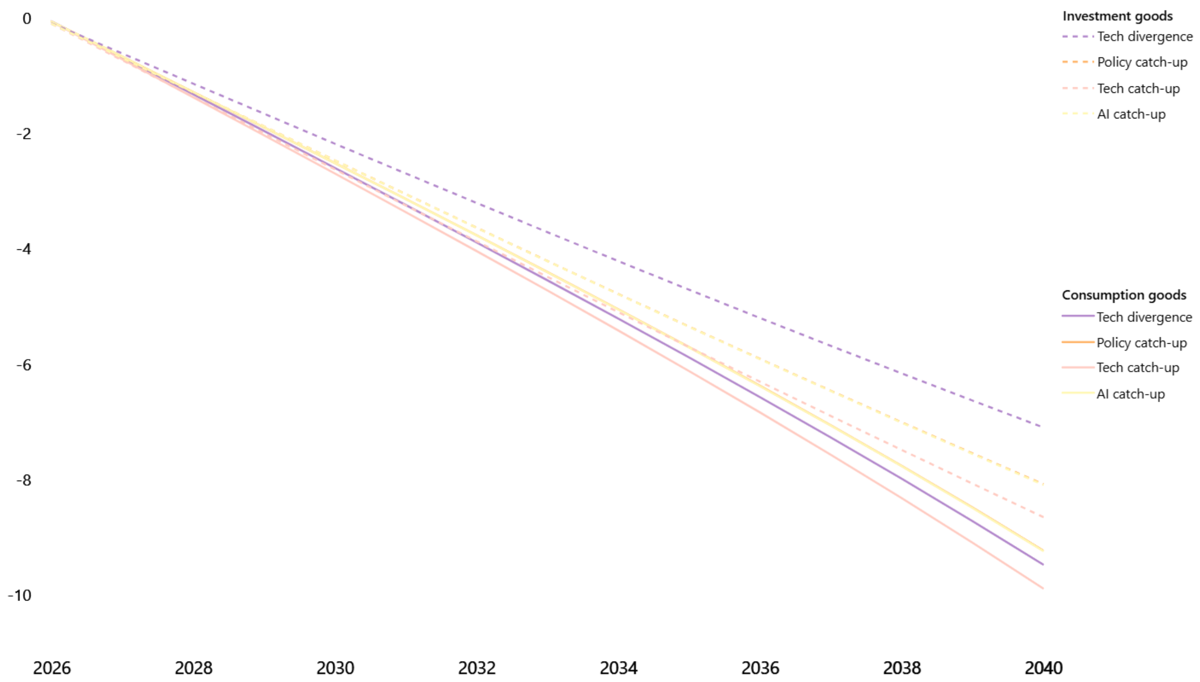
low-skilled workers. This implies that the positive impact of higher productivity on factor demand dominates the negative impact of the reallocation effect from labour towards AI for all production factors.

Second, these numbers imply that the real rental rate is projected to rise much more than the wage rates, raising the capital rental–wage ratio by more than 10% (see Figure A.2). The reason for this is that AI services, produced with both capital and labour, are replacing labour. This raises the demand for capital relative to labour and thus also the capital rental–wage ratio. This effect is reinforced by the fact that the production of AI services is relatively capital-intensive.

Third, between different types of workers, the real income of low-skilled workers is projected to increase the most, by 6.2% to 7.2%, while gains for medium- and high-skilled workers are about half as large. This implies that skill premium, the ratio of the wages of high-skilled to low-skilled workers, is projected to fall by 3%-4% (See Figure A.3). The reason is that shifts in tasks from labour towards AI are much stronger for high-skilled and medium-skilled workers than for low-skilled workers. As a result, the demand for high and medium-skilled workers falls relative to low-skilled workers. Furthermore, this result indicates that the variation in the reallocation of tasks between production factors dominates the variation in productivity growth and the degree of complementarity. The substitution elasticity between AI and labour is smallest for high-skilled workers and in *tech divergence* high-skilled workers incur the largest productivity growth. Nevertheless, high-skilled workers are projected to get the smallest productivity increases, indicating that the variation in the reallocation of tasks is quantitatively more important. In the robustness checks, we will further analyse whether a larger variation in the degree of complementarity can reverse the impact on wages of different skill types.

Before turning to the robustness checks, we explore whether changes in the price of investment goods compared to consumption goods can play a role in the projected change in the rental rate as in Caselli and Manning (2019). In theory, a decline in the price of investment

Figure 11: Changes in the Global Prices of Consumption and Investment Goods



Note: The figure displays the change in the global price of consumption and investment goods worldwide from 2025 to 2040 across four scenarios.

goods relative to consumption goods would put downward pressure on the rental rate of capital by making capital accumulation cheaper. However, Figure 11, displaying the change in the price of both investment goods and consumption goods, shows that although both consumption and investment goods prices fall over time, the decline is larger for consumption goods. For example, in *policy catch-up*, consumption goods prices drop by about 9 percent, compared with roughly 8 percent for investment goods. The reason is that both the projected productivity growth and, in particular, the projected trade cost reductions are larger in consumption sectors such as services compared to investment-intensive goods such as manufacturing. This implies that the relative price of investment goods actually rises slightly, which can help explain why the capital rental rates increase in our simulations: capital becomes relatively more expensive to accumulate, supporting higher returns.

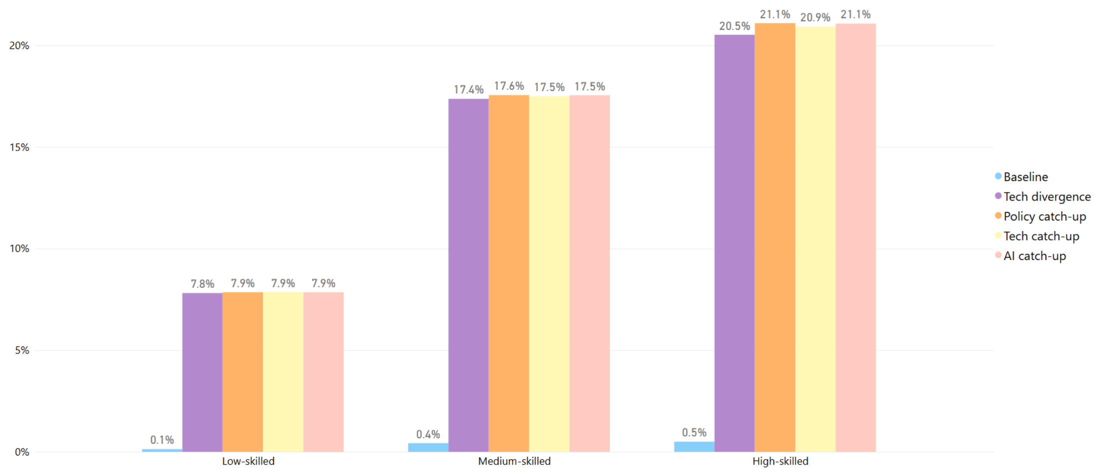
4.6 Robustness Tests

In this subsection, we vary key assumptions and parameters to test the robustness of our results and to gain more insights in the underlying mechanisms of our results. More specifically, we change the projected growth rate of the AI sector; the elasticities of substitution between capital and different types of labour-AI-service composites and between labour and AI services; and the assumed capital intensity of AI production. We evaluate for each of the variations how they impact the projected impact on trade, GDP and real factor prices.

4.6.1 Varying the growth rate of AI services

To test the robustness of our results to the assumed growth rate of the AI sector, we increase the growth of spending on AI services from 26% per year to 38% per year, based on UN Trade and Development (2025). Higher growth of the AI services sector without corresponding additional increase in the productivity gains from AI can be interpreted as a reduction in the economic efficiency of deploying AI. Figure 12 reports the shares of tasks performed using AI services across scenarios. On average, these shares increase to about 8% for low-skilled workers, 17% for middle-skilled workers, and 20% for high-skilled workers, compared to 3%, 7%, and 8%, respectively, in the benchmark. Higher growth will affect the projections on the three main outcome variables trade, GDP and real factor prices.

Figure 12: Robustness Checks: Share of AI Capital in AI-Capital-Labour Composite in 2040 with 38% Annual Growth in the AI Sector, by Labour-Skill Level.

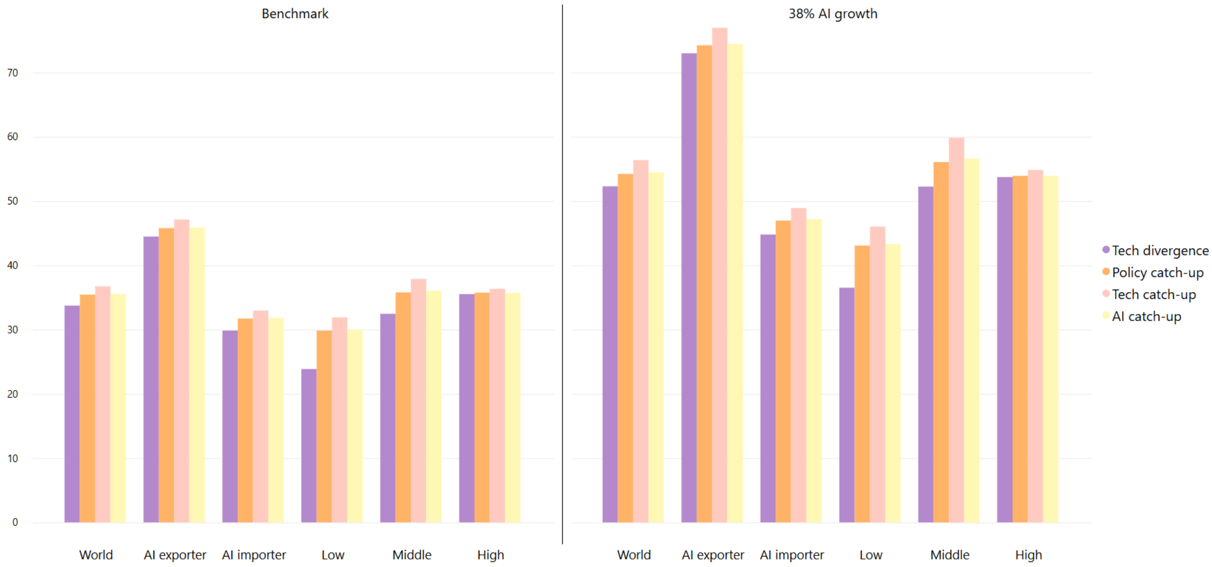


Notes: The figure displays the share of tasks which can be done with labour and AI, which are completed by AI, split by labour skill type, for four scenarios and the baseline scenario in which the growth of the AI sector is 38%.

First, Figure 13 shows that the projected trade growth is higher than in the benchmark with 26% annual growth in AI services. More specifically, the global increase in trade relative to the baseline exceeds 50%, whereas in the benchmark scenario this was about 35%. The reason for the larger increase is that the demand for AI services increases much more and the fact that AI services are highly tradable. This is clear from the fact that the increase in trade is largest for net exporters of AI services. However, also net importers of AI services see their trade increase compared to the benchmark scenario. This is because an increase in imports of AI services requires a concordant increase in exports to pay for these imports (reflecting the assumption of a fixed trade-balance-to-GDP ratio). Furthermore, the increased upstream demand for electronic equipment which is also highly tradable further fosters trade growth.

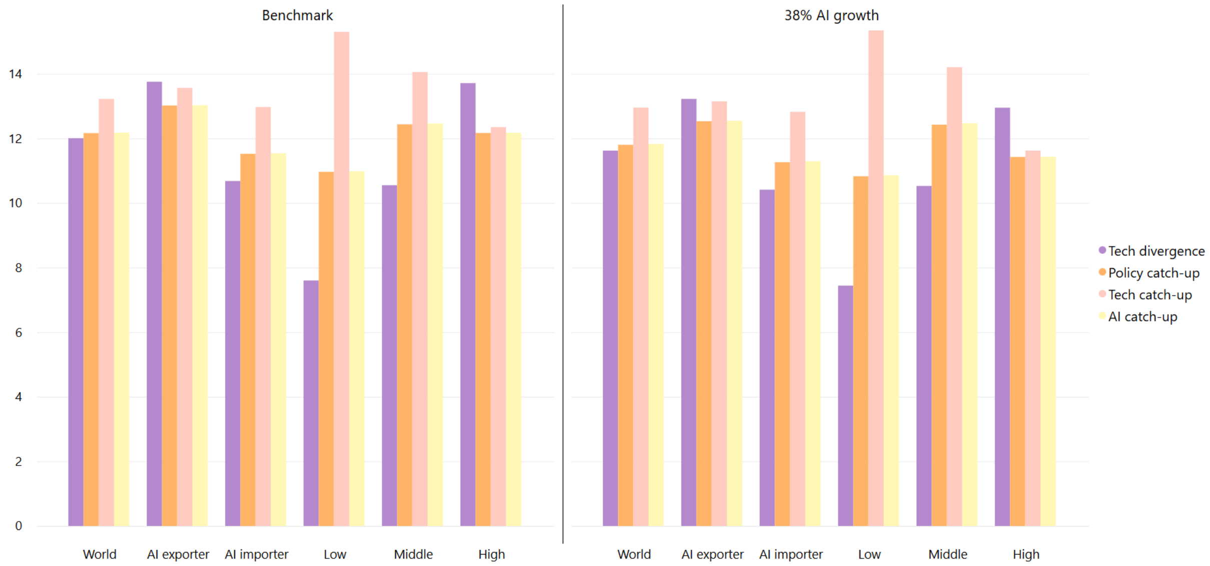
Second, the projected GDP growth is slightly smaller with 38% growth in AI services than with 26% growth (See Figure 14). The reason is that more AI services have to be produced, however, generating the same productivity growth. This implies that inputs are used less efficiently.

Figure 13: Robustness Checks: Changes in Real Exports with 38% Annual Growth in the AI Sector



Notes: this figure shows cumulative changes in real exports when the AI sector grows by 38% annually compared to 26% annually in the benchmark scenarios.

Figure 14: Robustness Checks: Changes in Real GDP with 38% Annual Growth in the AI Sector



Notes: this figure shows cumulative changes in real GDP when the AI sector grows by 38% annually compared to 26% annually in the benchmark scenarios.

Third, Figure 15 shows the projected change in real factor prices in the benchmark model on the left and in the model with 38% growth on the right. A larger growth in AI services has a profound impact on the projected changes in real factor prices. The rental rate rises almost twice as much (by 28.3 per cent instead of 18.4 per cent in the benchmark Tech catch-up scenario), whereas the change in real wages of medium-skilled and high-skilled workers switches from positive to negative, and the positive impact on low-skilled wages becomes substantially

Figure 15: Robustness Checks: Changes in Real Factor Prices with 38% Annual Growth in the AI Sector

Notes: this figure shows cumulative changes in real factor prices when the AI sector grows by 38% annually compared to 26% annually in the benchmark scenarios.

smaller.

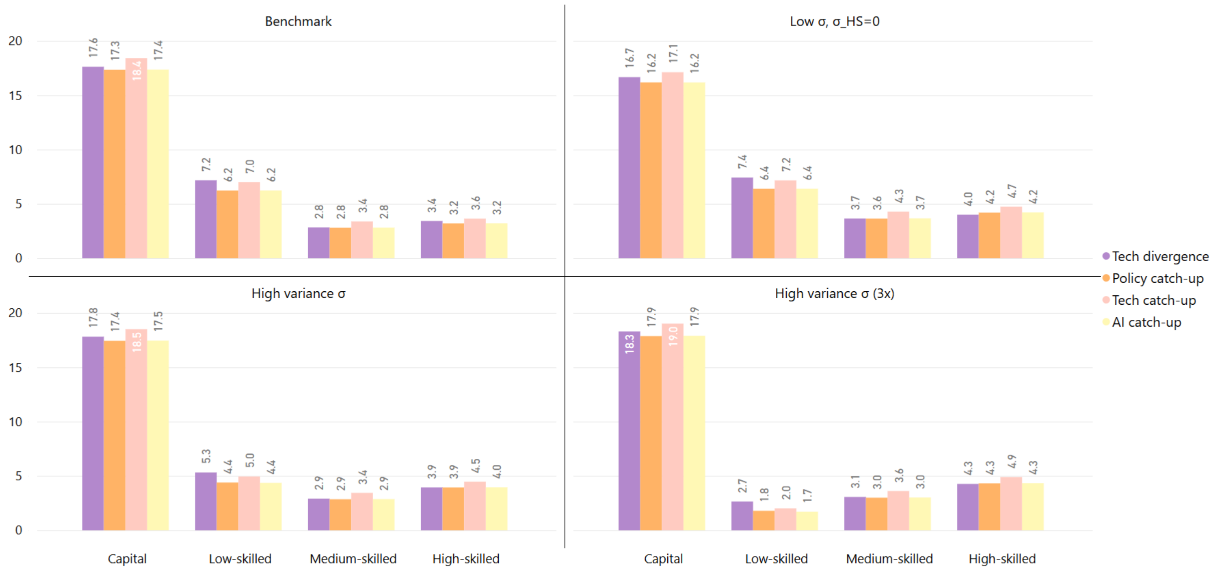
A larger growth rate of AI services magnifies the shift from labour to (capital-intensive) AI services, thus raising the positive impact on real rental rates and adversely impacting the projected change in real wages. Whereas in the benchmark lower AI growth scenario the positive output effect on all production factors dominates the reallocation effects, the latter effect dominates in the scenario with larger AI growth for high-skilled and medium-skilled workers who will see their real factor payments fall. However, low-skilled labour, which often involves manual or interpersonal tasks which are harder to automate by the existing AI, faces a smaller reallocation effect. As a result, the output effect dominates in both the default and higher growth scenarios.

4.6.2 Varying the substitution elasticities between labour and AI services

In this subsection, we examine how the degree of complementarity between labour and AI services for different skill types and between the labour-AI composite and capital affects the simulation results. More specifically, we vary the values of σ_s and κ, respectively, the substitution elasticities between labour and AI services and between the labour-AI composite and capital.

We start with an evaluation of the impact of the variation in σ_s across skill types. This robustness check is motivated by the fact that we do not have direct estimates of the substitution elasticity σ_s. Instead, σ_s is based on estimates of the degree of complementarity of occupations (aggregated to labour by skill types) with AI services. In the benchmark, we multiply these estimates for all skill types by 2 to ensure that the average elasticity is equal to the elasticity between value added and intermediates employed, which is set to be 0.9. However, the degree

Figure 16: Robustness Checks: Changes in Real Factor Prices with different variations in σ_s across skill types



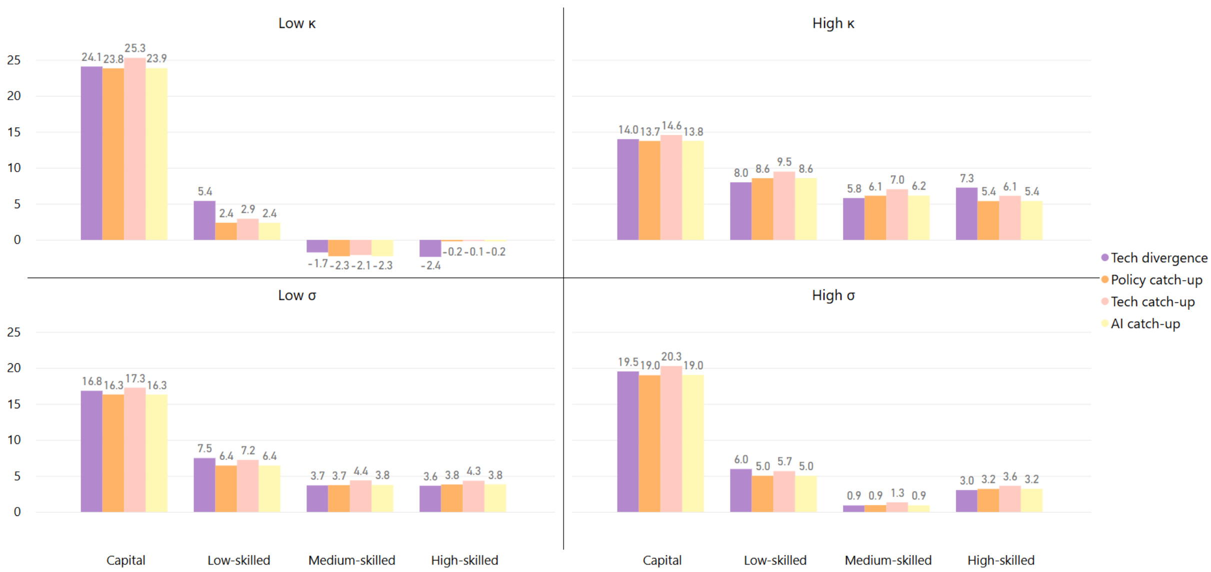
Notes: this figure shows cumulative changes in real factor prices with a larger variation in σ where $\sigma_{LS} = 2.32$ or $\sigma_{LS} = 3.49$ (3x), $\sigma_{MS} = 0.94$ and $\sigma_{HS} = 0.39$ or $\sigma_{HS} = 0.26$ (3x) and a low σ where $\sigma_{LS} = 0.58$, $\sigma_{MS} = 0.47$ and $\sigma_{HS} = 0$, all compared with the benchmark scenario.

of complementarity of occupations across skill types could also be mapped non-linearly into σ_s. Figure 16 displays the projected change in real factor prices for a higher variance in σ_s, a very high variance in σ_s and a specification setting σ_s equal to zero for high-skilled workers. The figure makes clear that a higher variance in σ_s reduced the difference in real income effects across skill types, whereas the pattern reverses for a very high variance in σ_s, implying that high-skilled workers gain more than low-skilled workers. However, the results do not change much compared to the benchmark in the setting with $\sigma_{HS} = 0$. Finally, the impact on the real rental rate on capital is hardly affected.

The results presented on a reverse impact on the skill premium with a very high variance in the different σ_s indicate that the degree of complementarity does play a role in the model as a counterweight to the variation in the reallocation of tasks for labour to AI services. On the one hand, the reallocation of tasks is highest for high-skilled workers, which exerts a downward pressure on their wages. On the other hand, high-skilled workers display more complementarity with AI services, which softens the downward pressure on their wages. Our model shows that one would need implausible parameter values for the complementarity channel to dominate the reallocation channel.

Next, we evaluate the impact of varying κ and σ_s separately. Figure 17 reports the cumulative impacts of AI on factor prices for low and high κ and for low and high σ_s. Across all scenarios, capital rental rates consistently record the largest gains, while low-skilled wages rise the most among the three labour types. A low κ widens the gap between the rental rate and the wage rates. Furthermore, middle-skilled and high-skilled workers may experience negative real wage changes. The reason is that the scope for substitution away from capital is limited, implying that it incurs a larger share of the gains. With a larger κ instead the rental-wage ratio rises less. Increasing or decreasing the elasticity of substitution between labour and AI services, σ_s, has only a small impact on the wage and rental rate impacts of AI.

Figure 17: Robustness Checks: Changes in Real Factor Prices with Varying κ and σ



Notes: this figure shows cumulative changes in real factor prices with low κ, where $\kappa = 0.6$, high κ, where $\kappa = 1.2$, low σ, where $\sigma_{LS} = 0.58$, $\sigma_{MS} = 0.47$ and $\sigma_{HS} = 0.26$ and high σ, where $\sigma_{LS} = 2.32$, $\sigma_{MS} = 1.78$ and $\sigma_{HS} = 1.04$.

Finally, we explore the impact of simultaneous changes in σ_s and κ in Figure 18. The upper right panel shows that a Cobb-Douglas structure with κ and σ_s equal to 1 has little impact on the benchmark results. However, in line with the results reported in the previous figure the disparity in real factor price impacts on capital and labour widen with small substitution elasticities, κ and σ_s, and falls when the substitution elasticities are higher.

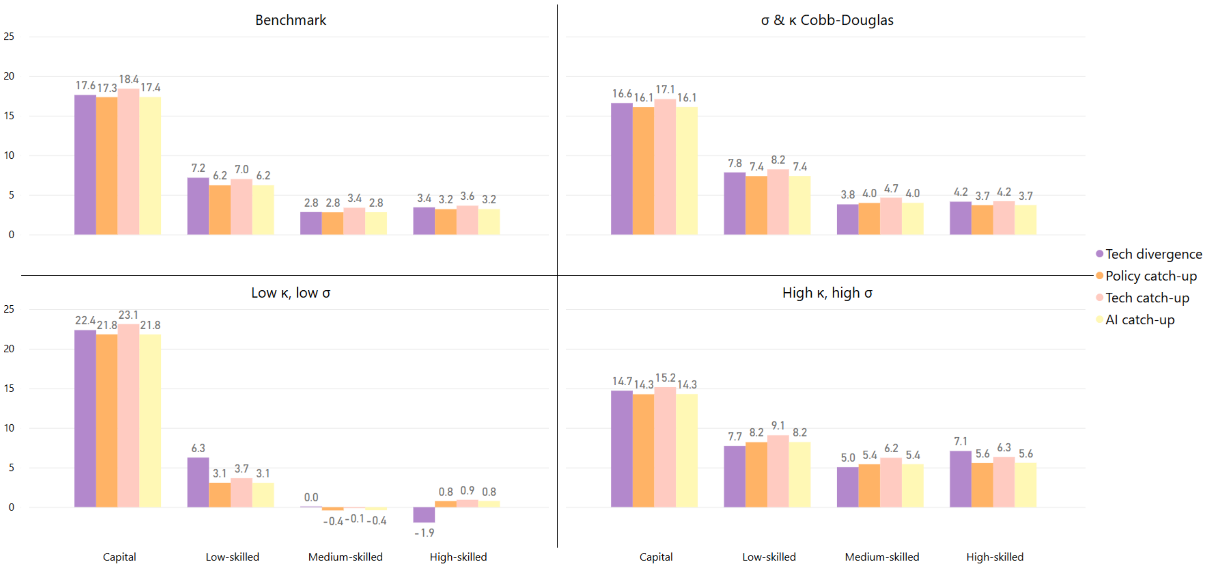
To conclude, the patterns in the benchmark results are robust to a range of variations in the substitution elasticities σ_s and κ. Depending on the parameters, the rental-wage ratio gap and the change in skill premium either become larger or smaller. The only exception holds for the setting with a very large variance in the labour-AI substitution elasticities across skill types, which could reverse the impact on the skill premium. However, this requires seemingly unrealistic variation in the substitution elasticities, i.e., $\sigma_{HS} = 0.26$ and $\sigma_{LS} = 3.49$.

In the annex, we show that the results for real GDP and real exports do not vary much with the values for σ_s and κ.

4.6.3 Low Capital Intensity of AI production

In this robustness check we change the construction of baseline data regarding the capital intensity of AI services. More specifically, we assume that capital intensity of AI services is identical to the ICT sector instead of 50% higher. We find that this lower capital intensity slightly reduces the magnitude of the increase in the capital rental rate by around 0.5% across all four scenarios, while the wages for all types of labour endowment increase by around 0.4%. In addition, we find that assuming a lower capital intensity for AI production does not significantly affect the patterns of output growth or trade volumes, as shown in the annex.

Figure 18: Robustness Checks: Changes in Real Factor Prices with Variation in Both κ and σ Together



Notes: this figure shows cumulative changes in real factor prices with σ and κ set to Cobb-Douglas, with $\kappa = 1$ and $\sigma = 0.99$, low κ and σ where $\kappa = 0.6$ and $\sigma_{LS} = 0.19$, $\sigma_{MS} = 0.15$ and $\sigma_{HS} = 0.09$, and high κ and σ, where $\kappa = 1.2$ and $\sigma_{LS} = 1.73$, $\sigma_{MS} = 1.34$ and $\sigma_{HS} = 0.78$.

5 Conclusion

In this paper, we examine the potential impacts of the development and deployment of AI on international trade, economic growth and the income distribution. We demonstrate that AI has significant potential to boost global GDP and trade by simultaneously reducing operational trade costs and increasing productivity across the economy through task automation. In our most optimistic scenario, global GDP rises by as much as 13.2 percent over the next fifteen years, and global trade volumes expand by about 35 percent. We find that the distribution of these gains across economies hinges on the improvement of digital infrastructure and the scope for technological catch-up for tasks automated with AI in low- and middle-income economies. We also show that AI can alter the income distribution within economies by (1) increasing the capital rental–wage ratio and (2) reducing the skill premium, although all production factors are projected to see their remuneration rise in real terms in the benchmark scenario for the growth of AI services.

We outline several promising directions for future research. First, in our framework, AI is used solely to complete existing tasks. Yet many scholars argue that AI will also create new tasks, both beneficial and harmful, which warrant further investigation (Acemoglu and Restrepo 2017; Acemoglu and Restrepo 2019; Acemoglu and Restrepo 2020b; Aghion and Bunel 2024). Second, we model the AI sector as perfectly competitive. Exploring the implications of potential market power in AI production could yield valuable insights for its impacts on growth and distribution. Third, more detailed input-output linkages for the AI services sector can be incorporated, as this will allow the researchers to obtain a more accurate projection of the upstream effects of AI as well as the impact of trade policies in this upstream sector on the economic effects of AI. For instance, AI training relies heavily on semiconductors, whose production is geographically concentrated in a few economies, and therefore, it would be valuable to have a separate semiconductors sector to understand more about the upstream impacts of AI expansion across regions. Similarly, given our finding that AI adoption may increase energy demand, examining its implications for emissions and climate policy would be an important extension. Finally, the interaction of AI and trade policy can be further explored, analysing both how the growth of AI can affect the impact of digital trade policies and how such policies can impact the ability of economies to exploit the productivity gains and trade cost reduction potential of AI.

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Appendix A Further Details of Model Description

Appendix A .1 Disaggregated sectors and regions

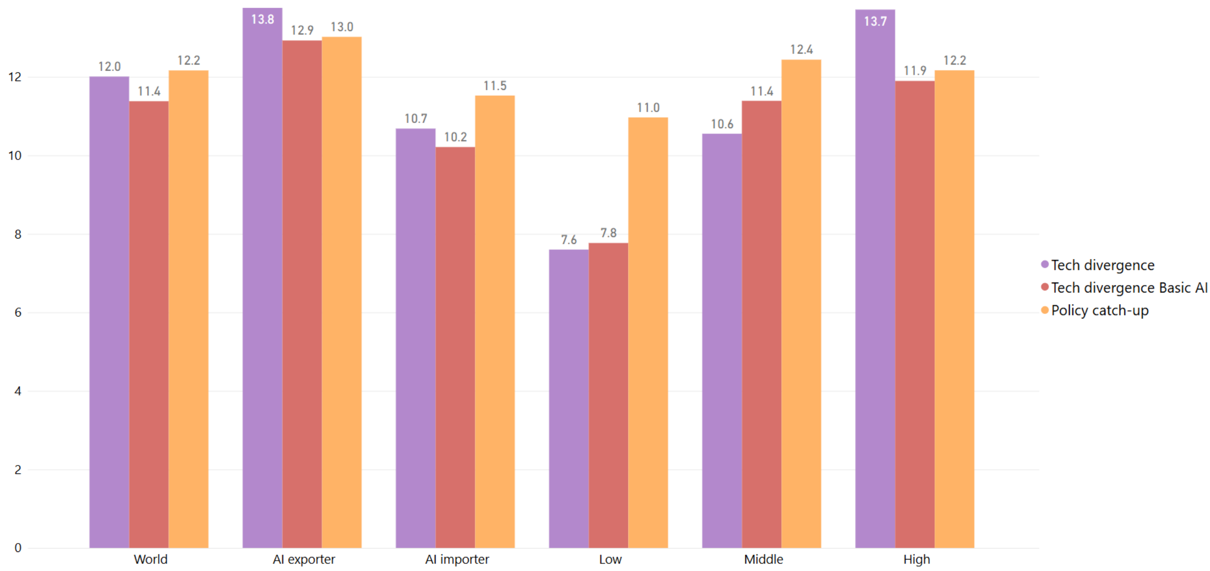
Agg Sector	**Sector Name**	**Corresponding Commodities (ISIC Rev. 4)**
AGC	Agriculture	01T02 Agriculture, hunting, forestry; 03 Fishing and aquaculture
MXT	Mining (Energy)	05T06 Mining and quarrying, energy producing products
MIN	Mining (Non-energy)	07T08 Mining and quarrying, non-energy producing products; 09 Mining support service activities
OTG	Other Goods	10T12 Food products, beverages and tobacco; 13T15 Textiles, textile products, leather and footwear; 16 Wood and products of wood and cork; 17T18 Paper products and printing; 20 Chemical and chemical products; 21 Pharmaceuticals, medicinal chemical and botanical products; 22 Rubber and plastics products; 23 Other non-metallic mineral products; 31T33 Manufacturing nec; repair and installation of machinery and equipment
PCH	Coke and Petroleum	19 Coke and refined petroleum products
MET	Metals	24 Basic metals; 25 Fabricated metal products
COM	Computers and Other Electronic Parts	26 Computer, electronic and optical equipment
ELE	Electrical Equip.	27 Electrical equipment
MEQ	Machinery	28 Machinery and equipment, nec; 29 Motor vehicles, trailers and semi-trailers; 30 Other transport equipment
ELY	Electricity	35 Electricity, gas, steam and air conditioning supply
UTC	Utilities/Construction	36T39 Water supply; sewerage, waste management and remediation activities; 41T43 Construction
TRA	Trade Support Services	45T47 Wholesale and retail trade; repair of motor vehicles; 52 Warehousing and support activities for transportation
TRP	Transport	49 Land transport and transport via pipelines; 50 Water transport; 51 Air transport
OBS	Other Business Services	53 Postal and courier activities; 58T60 Publishing, audiovisual and broadcasting activities; 64T66 Financial and insurance activities; 68 Real estate activities; 69T75 Professional, scientific and technical activities; 77T82 Administrative and support services
ICT	Information and Communications Technology Services	61 Telecommunications; 62T63 IT and other information services
OTS	Other Services	55T56 Accommodation and food service activities; 84 Public administration and defence; compulsory social security; 85 Education; 86T88 Human health and social work activities; 90T93 Arts, entertainment and recreation; 94T96 Other service activities; 97T98 Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Table A.1: Aggregated sectors, their full names, and corresponding ISIC Rev. 4 commodities.

Agg Region	**Region Name**	**Economies and Regions**
LAC	Latin America and the Caribbean	Argentina, Chile, Colombia, Costa Rica, Peru
ODE	Other Developed Economies	Australia, Switzerland, Iceland, Norway, New Zealand
WEU	Western European Union Members	Austria, Belgium, Germany, Denmark, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Sweden
SLD	Low-income Developing Economies in Asia	Bangladesh, Cambodia, Lao People's Democratic Republic, Myanmar
EEU	Europe Union Members	Bulgaria, Cyprus, Czech Republic, Estonia, Croatia, Hungary, Lithuania, Latvia, Poland, Romania, Slovak Republic, Slovenia
ROW	Rest of the World	Republic of Belarus, Kazakhstan, Pakistan, Rest of World aggregate, Ukraine
BRA	Brazil	Brazil
SEA	Southeast Asia	Brunei Darussalam, Indonesia, Malaysia, Philippines, Singapore, Thailand, Viet Nam
CAN	Canada	Canada
CHN	China	People's Republic of China
SSA	Sub-Saharan Africa	Côte d'Ivoire, Cameroon, Nigeria, Senegal, South Africa
MNA	Middle East and North Africa	Egypt, Israel, Jordan, Morocco, Kingdom of Saudi Arabia, Tunisia
GBR	United Kingdom	United Kingdom
EAS	The Rest of East Asia	Hong Kong, China; Chinese Taipei
IND	India	India
JPN	Japan	Japan
KOR	Republic of Korea	Republic of Korea
MEX	Mexico	Mexico
RUS	Russian Federation	Russian Federation
TUR	Türkiye	Türkiye
USA	United States	United States of America

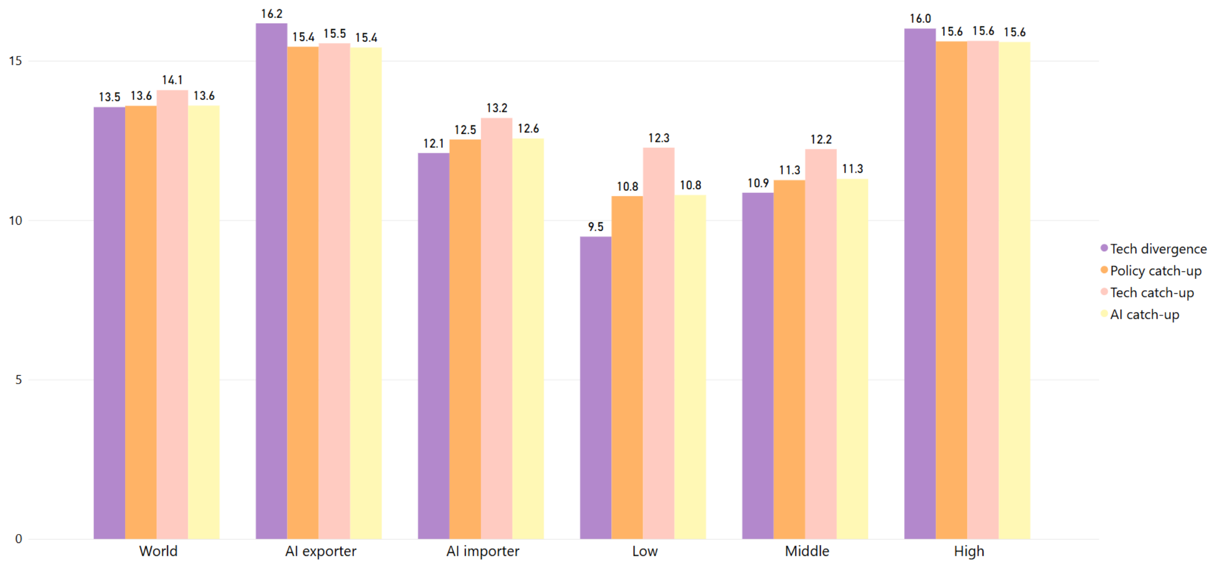
Table A.2: Aggregated regions, their descriptions, and corresponding economies

Figure A.1: Change in real GDP in Tech Divergence with Basic AI



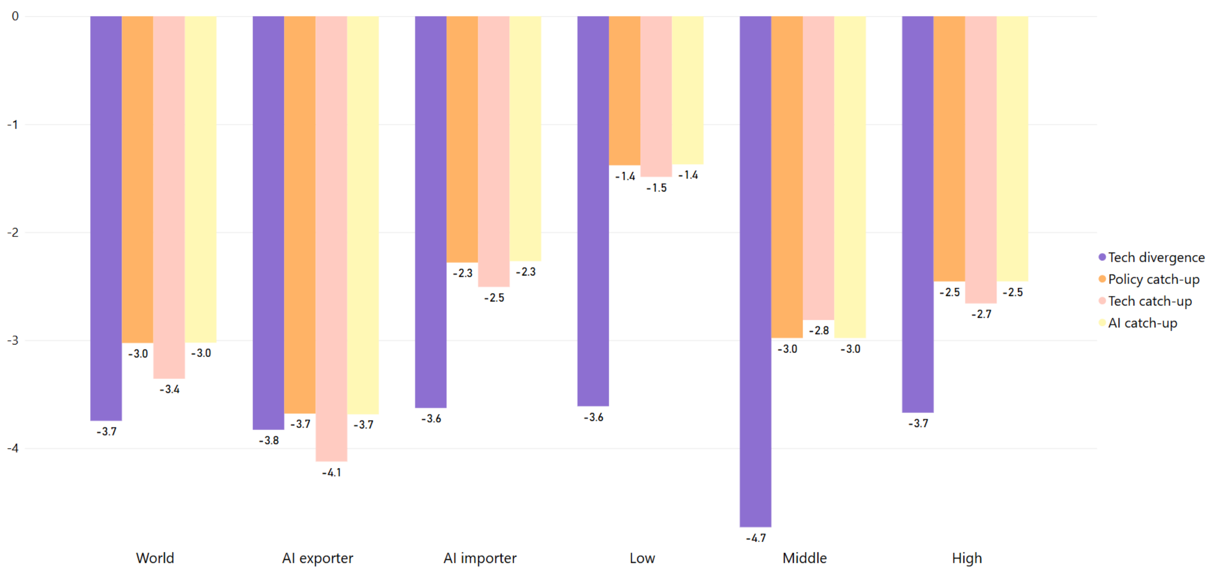
Notes: this figure shows the cumulative change in real GDP globally, by AI exporter/importer and across income groups in the Tech divergence scenario with Basic AI compared to the benchmark Tech divergence with Advanced AI and Policy catch up scenarios. Moving from Advanced to Basic AI reduces the GDP gains for the high income group as these economies are high skill intensive and therefore average productivity gains are smaller.

Figure A.2: Cumulative Change in Global Rental-to-Wage Ratio in the Benchmark



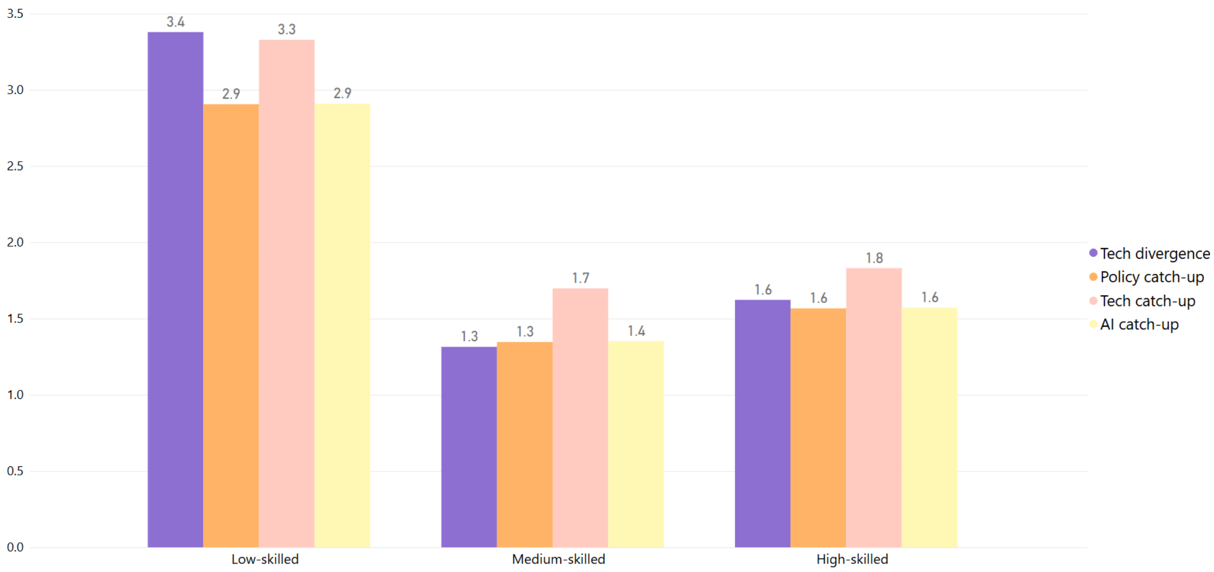
Notes: The figure displays the cumulative change in the global rental-to-wage ratio (the difference between the change in the rental rate and the average change in wages across skill types) over 2025-2040 for four scenarios in deviation from the baseline.

Figure A.3: Cumulative Change in the Skill Premium over 2025-2040



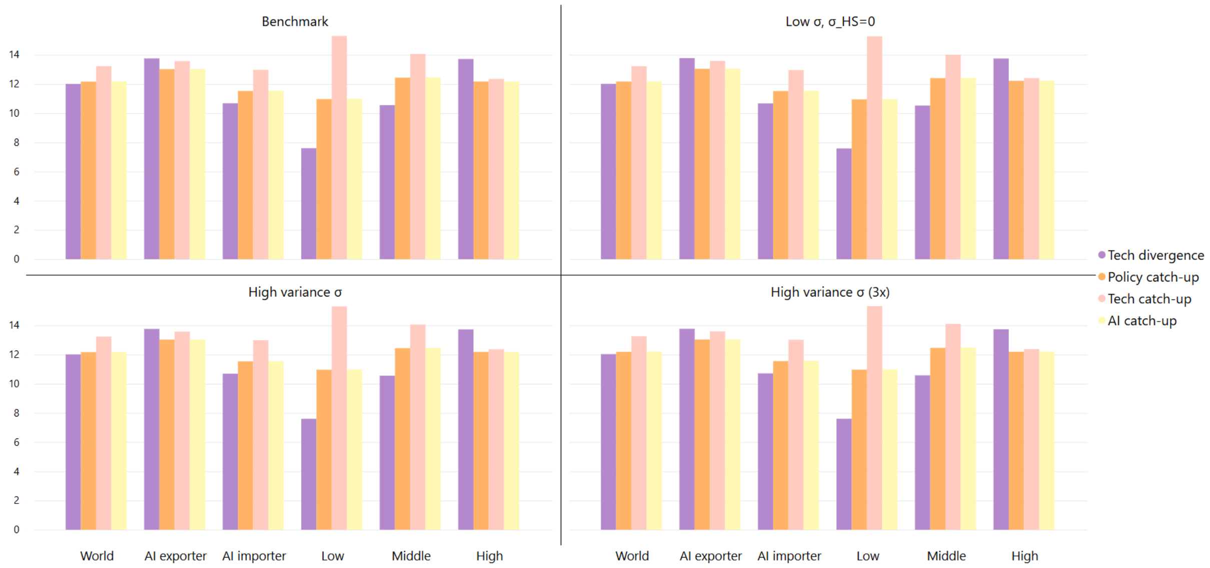
Notes: The figure displays the change in the skill premium, the difference in wage between high- and low-skilled workers, for four scenarios in deviation from the baseline, both globally and for aggregate regions, split by income level and between AI net exporters and AI net importers. AI net exporters and net importers are defined by calculating net exports (exports minus imports) in AI for each region.

Figure A.4: Changes in Employment, by Skill Level



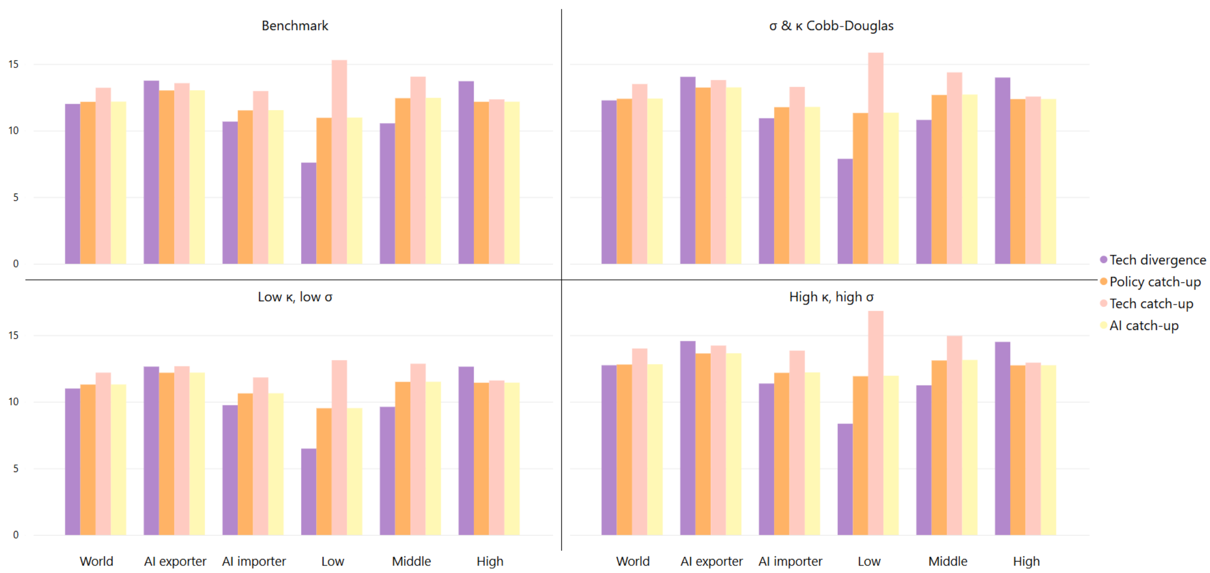
Note: The figure displays the cumulative change in employment by 2040 in the four scenarios, in deviation from baseline.

Figure A.5: Robustness Checks: Changes in Real GDP with Varying σ



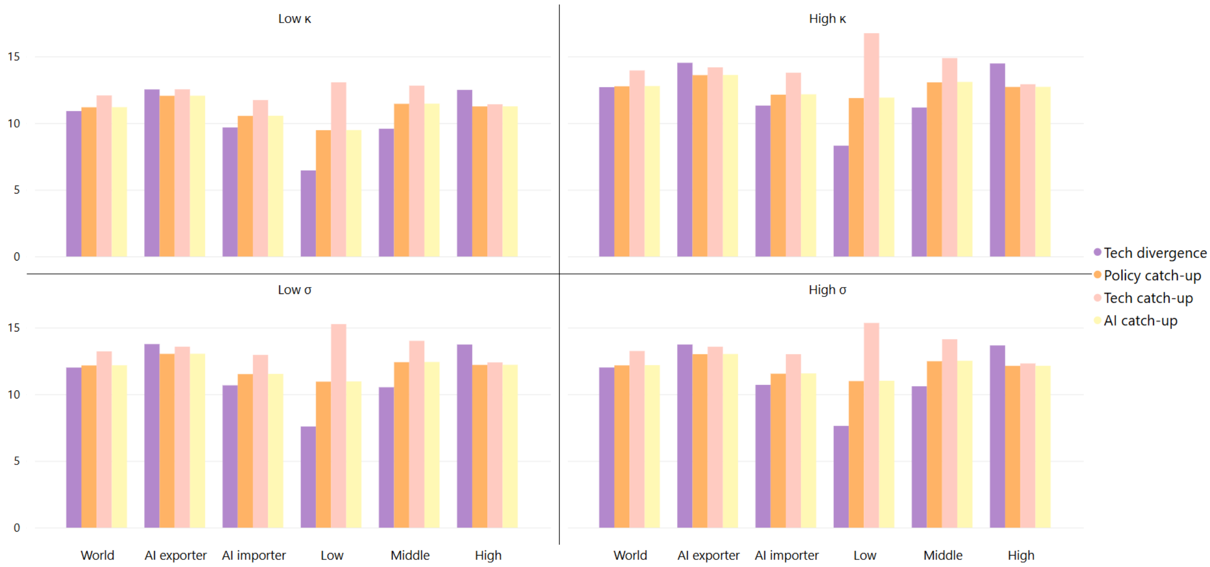
Notes: this figure shows cumulative changes in real GDP with a larger variation in σ where $\sigma_{LS} = 2.32$ or $\sigma_{LS} = 3.49$ (3x), $\sigma_{MS} = 0.94$ and $\sigma_{HS} = 0.39$ or $\sigma_{HS} = 0.26$ (3x) and a low σ where $\sigma_{LS} = 0.58$, $\sigma_{MS} = 0.47$ and $\sigma_{HS} = 0$, all compared with the benchmark scenario.

Figure A.6: Robustness Checks: Changes in Real GDP with Variation in Both κ and σ Together



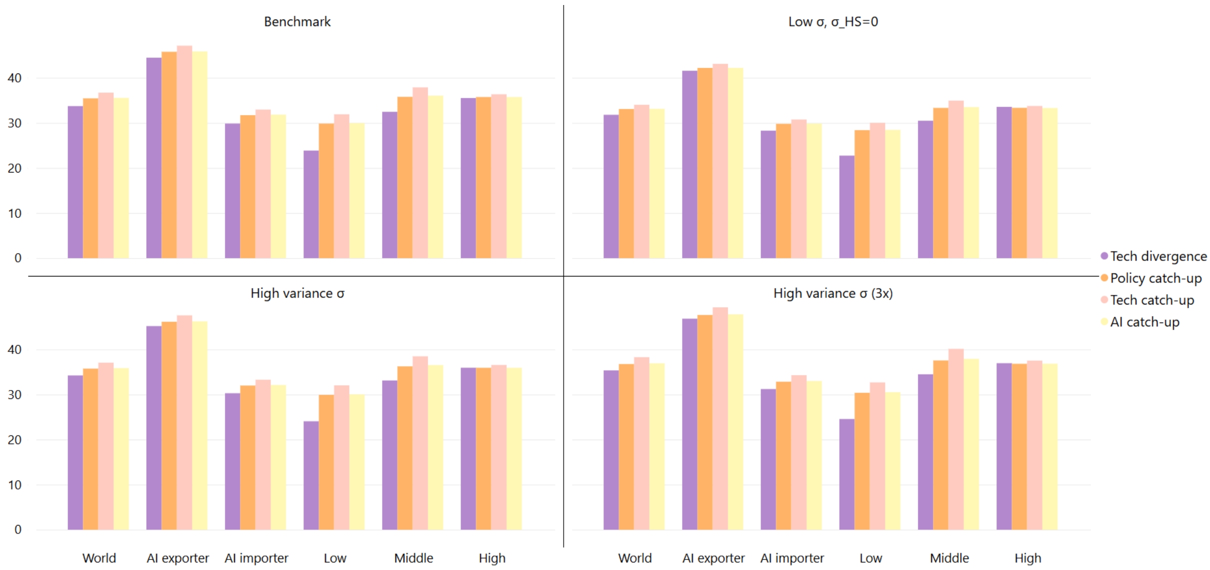
Notes: this figure shows cumulative changes in real GDP with σ and κ set to Cobb-Douglas, with $\kappa = 1$ and $\sigma = 0.99$, low κ and σ where $\kappa = 0.6$ and $\sigma_{LS} = 0.19$, $\sigma_{MS} = 0.15$ and $\sigma_{HS} = 0.09$, and high κ and σ, where $\kappa = 1.2$ and $\sigma_{LS} = 1.73$, $\sigma_{MS} = 1.34$ and $\sigma_{HS} = 0.78$.

Figure A.7: Robustness Checks: Changes in Real GDP with Varying κ and σ



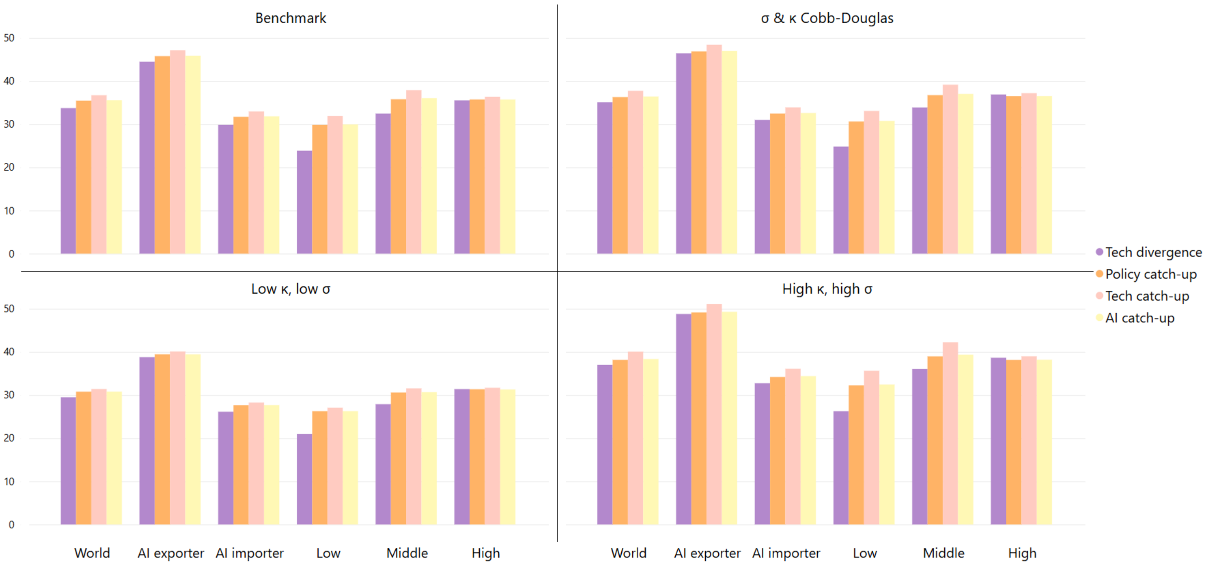
Notes: this figure shows cumulative changes in real GDP with low κ, where $\kappa = 0.6$, high κ, where $\kappa = 1.2$, low σ, where $\sigma_{LS} = 0.58$, $\sigma_{MS} = 0.47$ and $\sigma_{HS} = 0.26$ and high σ, where $\sigma_{LS} = 2.32$, $\sigma_{MS} = 1.78$ and $\sigma_{HS} = 1.04$.

Figure A.8: Robustness Checks: Changes in Real Exports with different Variation in σ_s across Skill Types



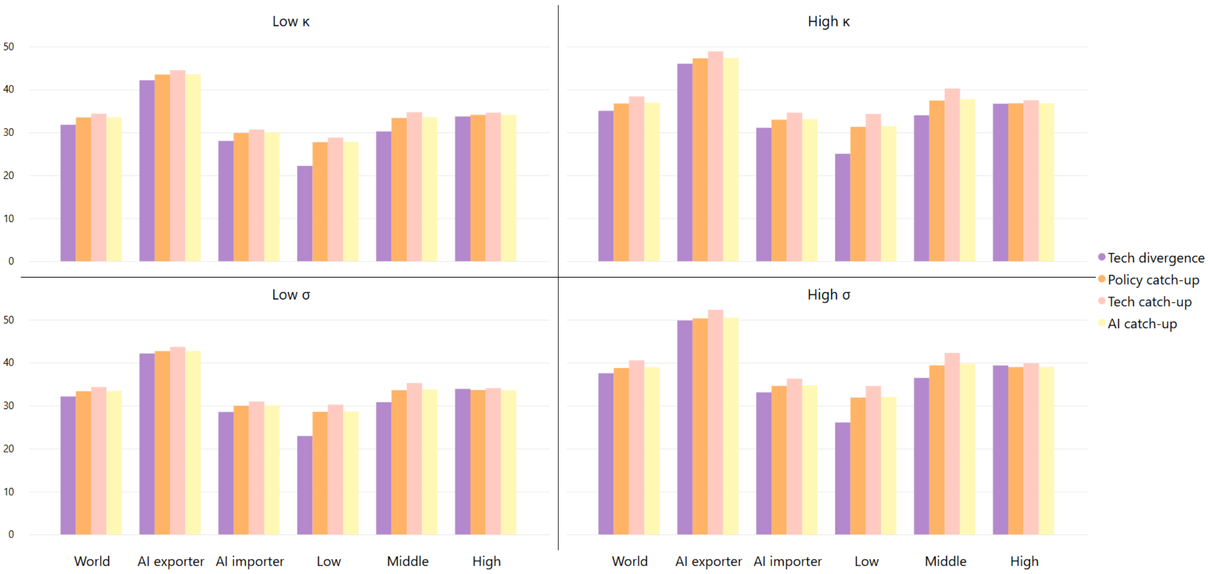
Notes: this figure shows cumulative changes in real exports with a larger variation in σ where $\sigma_{LS} = 2.32$ or $\sigma_{LS} = 3.49$ (3x), $\sigma_{MS} = 0.94$ and $\sigma_{HS} = 0.39$ or $\sigma_{HS} = 0.26$ (3x) and a low σ where $\sigma_{LS} = 0.58$, $\sigma_{MS} = 0.47$ and $\sigma_{HS} = 0$, all compared with the benchmark scenario.

Figure A.9: Robustness Checks: Changes in Real Exports with Variation in Both κ and σ Together



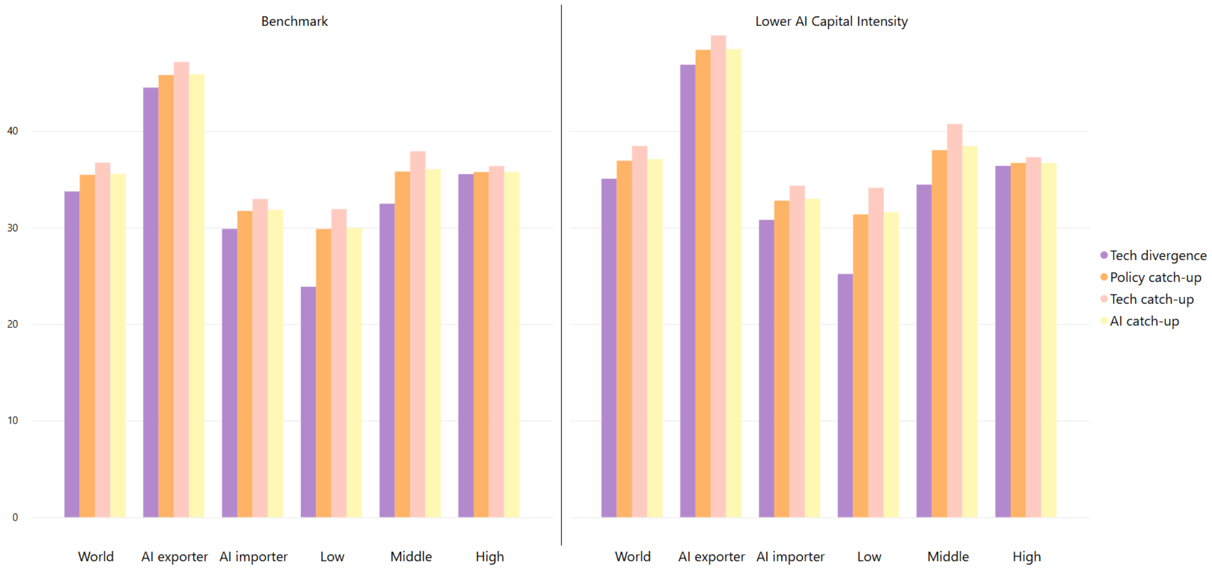
Notes: this figure shows cumulative changes in real exports with σ and κ set to Cobb-Douglas, with $\kappa = 1$ and $\sigma = 0.99$, low κ and σ where $\kappa = 0.6$ and $\sigma_{LS} = 0.19$, $\sigma_{MS} = 0.15$ and $\sigma_{HS} = 0.09$, and high κ and σ, where $\kappa = 1.2$ and $\sigma_{LS} = 1.73$, $\sigma_{MS} = 1.34$ and $\sigma_{HS} = 0.78$.

Figure A.10: Robustness Checks: Changes in Real Exports with Varying κ and σ



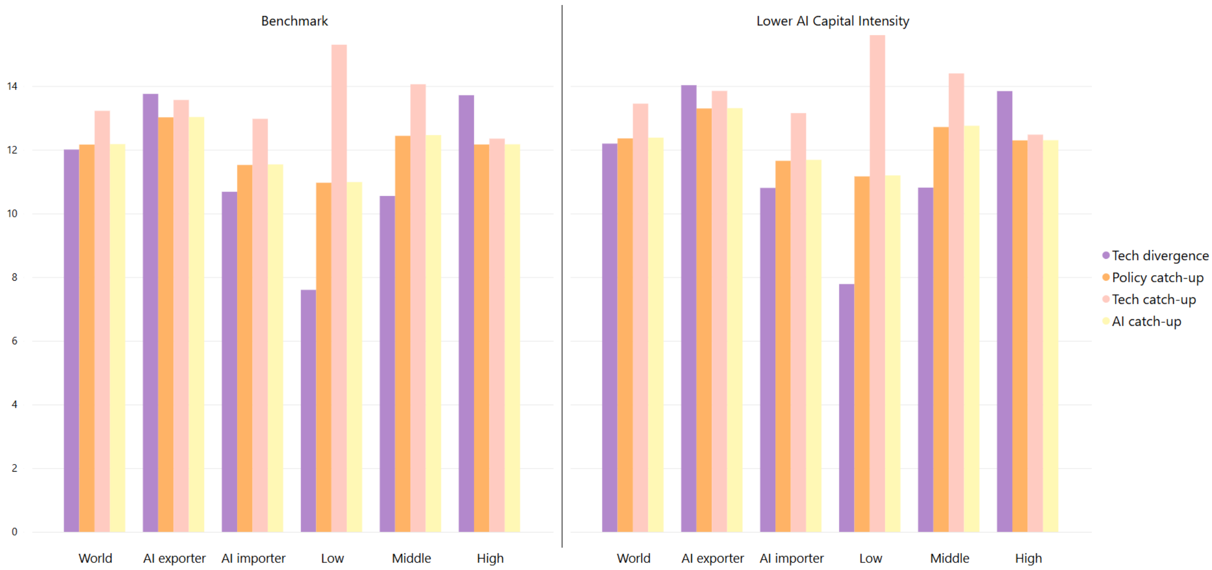
Notes: this figure shows cumulative changes in real exports with low κ, where $\kappa = 0.6$, high κ, where $\kappa = 1.2$, low σ, where $\sigma_{LS} = 0.58$, $\sigma_{MS} = 0.47$ and $\sigma_{HS} = 0.26$ and high σ, where $\sigma_{LS} = 2.32$, $\sigma_{MS} = 1.78$ and $\sigma_{HS} = 1.04$.

Figure A.11: Robustness Checks: Changes in Export Volume with Lower Capital Intensity in the AI sector



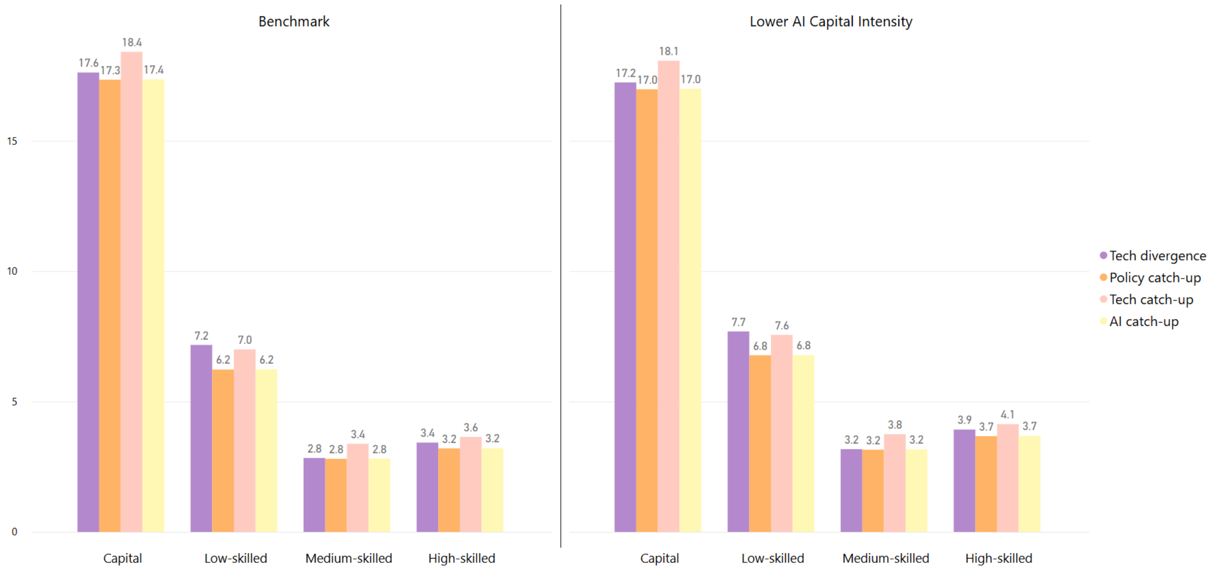
Notes: this figure shows cumulative changes in export volume when the AI sector with lower capital intensity compared to the benchmark case.

Figure A.12: Robustness Checks: Changes in GDP with Lower Capital Intensity in the AI sector



Notes: this figure shows cumulative changes in GDP when the AI sector with lower capital intensity compared to the benchmark case.

Figure A.13: Robustness Checks: Changes in Real Factor Prices with Lower Capital Intensity in the AI sector



Notes: this figure shows cumulative changes in real factor prices when the AI sector with lower capital intensity compared to the benchmark case.